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# Active Learning Observation Networks

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**Abstract.** Classroom observation protocols have been used to gauge the types of actions made by students and teachers in classrooms. In this study, we illustrate a novel method for encoding an observation protocol of teacher and student actions during a lesson into a network representation. We divide lessons into 30s interval and characterize each interval with a combination of 35 codes which depict different aspects of actions. Combined codes from each interval are used to create what we label an observation network - based on the temporal ordering of our combined codes. We then use community detection to create a network map of the observation network and provide an interpretation of the network map. We argue that our novel method can be used to investigate the dynamics of teaching in different classrooms for different teachers in different contexts.

**Keywords:** Teaching and Learning, Observation Protocols, Network Analysis.

## 1 Introduction

Classroom observations protocols have been used to gauge the types of actions made by students and teachers in classrooms [1–5]. Analyses based on protocol observations have been used in middle and high school settings (e.g., [4]) as well as university settings to summarize teaching. We argue that encoding and portraying observations of student and teacher actions in networks, may expand the use of observation protocols to capture the dynamics of teaching [6].

The purpose of this poster is twofold. First, we illustrate how we encode video observations to network maps via an expanded version of the Classroom Observation Protocol for Undergraduate STEM (COPUS) [1]. Second, we show an example network and a network map, which illustrate how observation networks may be used to analyze a lesson. Our example comes from a Danish project which developed and investigated high school physics teaching. The example network and network map of this study stems from video observations of one of the lessons from the project.

## 2 Encoding Video Observations as Networks

We argue that the flow and structure of a lesson can be captured in networks of observation codes. The original COPUS protocol was developed to capture classroom behaviors in university settings and consists of 13 codes for "what students are doing" (e.g., listening, group work, discussing clicker questions) and 12 codes for what the teacher is doing (e.g., lecturing, demonstrating experiment, asking clicker questions). We expanded on the number of codes to 35 within 6 categories: mode, student activity, verbal interactions, subject matter, and curricular goals, and other. The reasons for these changes were that they better capture the dynamics of a Danish upper secondary classroom than does the original COPUS protocol (see Table 1 for a list and brief explanation of all codes). For instance, *mode* was subdivided into blackboard centered, table centered, computer centered, and experiment centered. The actions of teachers and students may signify different things and lead to different learning outcomes in different modes. For example, a teacher making a statement when the teaching is blackboard centered is different from a teacher making a statement teaching is centered around work on a computer; the former may be suited for a formal explanation, while a formal explanation in the latter context may not be given the same attention by students.

The COPUS protocol utilizes 2-minute time intervals to document classroom behaviors, meaning that coders watch 2 minutes of video and then code that. We found that drastic changes in teaching could happen during shorter intervals [7], and we settled on 30 second intervals instead.

Our protocol recognizes that teaching and learning encompasses more than what the students and the instructor explicitly do, but also shifting modalities of teaching such as going from blackboard to table centred modalities or non-curriculum related actions. In order to capture these shifting modalities, we converted the filled-out observation protocols to an observation network, which captures the flow and structure of a lesson.

Our strategy is to concatenate codes and create networks of these concatenated codes to capture the overarching structure of teaching in classrooms. The process of concatenation is as follows: Each 30-second time interval consists of a number of codes assigned by the observer. Each of these codes are given a short name (for instance *b* for *blackboard centered* and *Tsay* for teacher statement). If codes co-occur during a 30-second interval, they are combined into a single code (for instance, *b Tsay* to code for a teacher making a statement at the blackboard). This produces a set of unique concatenated codes. These are represented as nodes (circles) in our network. A directed link (represented by and arrow) is drawn between two concatenated codes, if one code follows the other in the protocol (See Fig. 1).

**Table 1.** Categories and subcategories for our extended version of the COPUS protocol.

| Category | Subcategories | Description |
|---|---|---|
| Mode | Blackboard, table, computer or experiment centered | Whether the teaching is centered on the blackboard, students working at a table, on a computer, or with an experimental setup. |
| Student activity | Listen/look, read/seek information, calculation/perform task, hypotheses/planning experiment, carry experiment, presentations | Descriptions of overall tasks students are doing in class. These are the types of learning activities that students were observed to do. |
| Verbal interaction | Teacher/student-ask-teacher/student-answer (all permutations), teacher-ask-group-answer, teacher/student statement, group dialogue, group teacher dialogue | Ask-answer patterns: e.g., when a teacher/student asks a clear question and receives a clear answer. Statements as lengthy expositions. Dialogue when actors take turns and react to each other's statements. |
| Curricular content | The universe, the solar system, subject atoms, descriptions/examples of energy, the wave equation, the electromagnetic spectrum, other sound and light | Subject contents of the curriculum. Here presented as headlines. |
| Curricular learning outcomes | Modelling, experimentation, presentation, perspectives, dissemination, knowledge of methods, knowledge of interdisciplinary aspects | Intended learning outcomes of curriculum. Here presented in short form. |

In this way, the network depicts the flow of the lesson as described by codes. In the observation network, thicker links between two concatenated codes indicate that one follows the other more times (the thicker the link the more times). The size of the nodes indicates how many times that particular node has been used, which is equivalent to the time spent in the classroom on that particular combination of codes. Figure 2 (Top) shows the resulting network for an observed lesson.

| time | observation | code |
|---|---|---|
| 00:00:00-00:02:30 | Computer-centered context, where the teachers gives instruction not directly related to the curriculum | c_Tsay_naa |
| 00:02:30-00:03:00 | Computer-centered context, a student asks a question, the teacher and other students answer. Not curricular. | c_SqTa+SqSa+Tsay_naa |
| 00:03:00-00:03:30 | Computer-centered context, where the teachers gives instruction not directly related to the curriculum | c_Tsay_naa |
| 00:03:30-00:04:00 | Computer-centered context, students log into the game, groups discuss how to do it, teacher informs. | c_seek_Tsay+GrDi_naa |

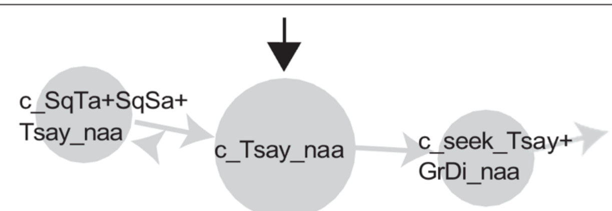


**Fig. 1.** Example of how we generate observation networks.

## 3 Example of Structure and Flow of a Lesson

A detailed analysis of the observation network reveals valuable information about the lesson (for instance, the large brown node signifies that a lot of time is spent on group work about models of energy on the computer). However, we can simplify the network by applying a flow-based community detection algorithm [8] to create maps of lesson structure and flow. Network analyses offers a variety of different algorithms for detecting communities. In choosing a flow-based algorithm, we assume that the ordering of teaching activities holds valuable in- formation about the dynamics of teaching (see [8] for a further discussion of the differences between community detection algorithms). Figure 2 shows one such network and map. Each circle in the map corresponds to a subset of the observation network. We use this subset to name the module. The map provides an overview of the lesson. Here, each circle, or module, represents a sub-network of codes. The size of circles now represent flow through the links in and between modules (see e.g., [9] for a detailed explanation of the algorithm in an educational context). We have given each module an interpretative name that reflects our understanding of each sub-network. The network map depicts teaching, which is largely driven by students, but framed by the teacher. This method may impact the way classroom observations are conducted and analysed and may form the basis for detailed analyses of the dynamics of teaching in different classrooms for different teachers in different contexts.

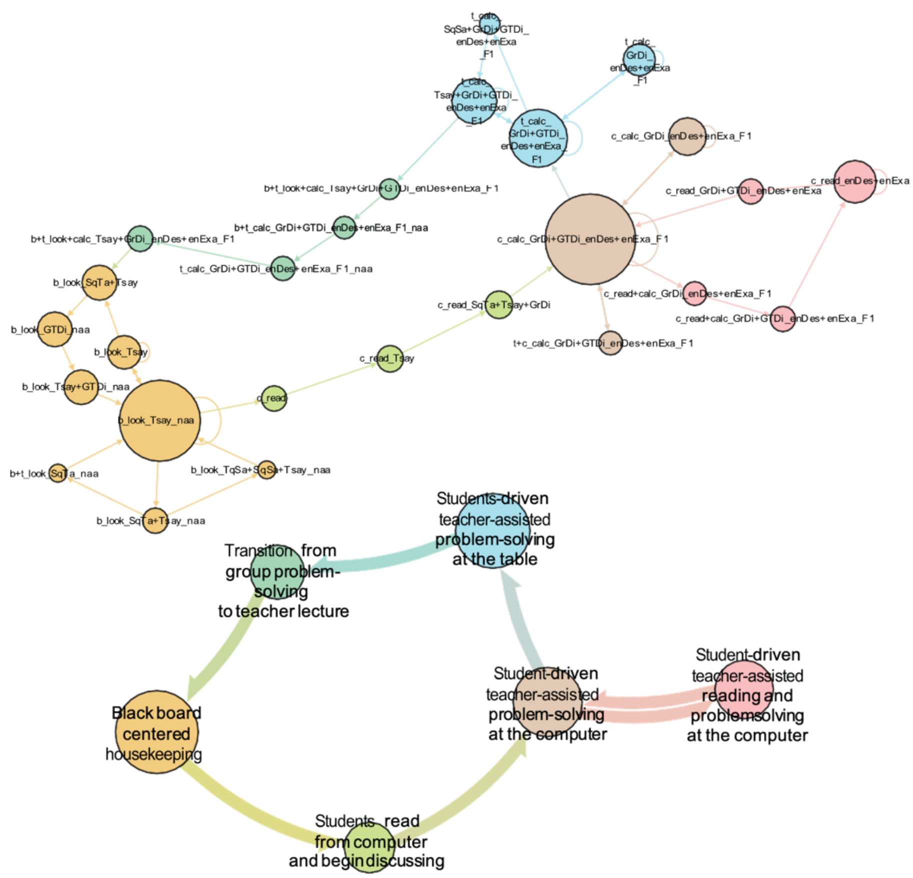


**Fig. 2.** (Top) An observation network for a lesson involving two major teaching/learning activities: A problem to be solved on the computer by student groups and a problem to be solved on paper by student groups. (Bottom) The network map of the same lesson with module names based on our interpretation of the underlying subset of codes [7].

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# Learning software development on the Web: Exploring Patterns in Students' Platform Access Traces

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**Abstract.** The multitude of platforms available on the Web have radically changed education and learning. Therefore, a good understanding of how Web-based resources are used by undergraduate students' for learning disciplinary knowledge and skills is paramount. This empirical study explores computer and software engineering students' use of the Web-based resources during a three-month period, while they work on semester-long software development projects. The study presents an analysis of digital traces of the use of multiple online platforms, in combination with self-reported data, through latent class analysis and latent profile analysis. Preliminary findings reveal distinct patterns in students' use of the Web, as well as differences in the way such patterns become visible during the semester. The study contributes to a better understanding of students' use of online platforms for learning. Methodologically, it illustrates how traces from the Web can be used to study such learning.

**Keywords:** Online Platforms, Digital Traces, Informal Learning, Undergraduate Education, Software Development.

## 1 Introduction

The Web, an open architecture of protocols, has radically changed undergraduate education and learning by enabling students to create findable and linkable online platforms [1]. Educational research has extensively studied the use or implementation of studying single platforms (e.g., Facebook, Twitter or WhatsApp) in relation to curriculum-based tasks to support students [2]. While these studies show that platforms can support student learning in multiple ways, they focus less on how students (outside the task or curriculum defined boundaries) navigate the Web to access platforms they consider relevant for their learning [3]. Moreover, research based on students' self-reports suggests they informally use several platforms to work on curriculum-based tasks [4]. Yet, the studies addressing the informal use of online platforms do not provide empirical evidence and in-depth understanding of such use. In addition, these studies do not take into account that students might navigate the Web in different ways depending on the tasks they face, the period of the semester they find themselves in, and/or the disciplinary domain of their studies. While some disciplinary domains, such as computer and software engineering (CSE), have integrated several platforms into their work [5], research on learning involving the use of such platforms is limited [3]. This study aims to contribute a better understanding of how students informally navigate the Web to access and use resources available on (multiple) online platforms both in domain-specific contexts and over (curricular) time. The study poses the following research questions:

RQ1: How do CSE students use the Web to access online platforms to learn software development? This question is answered by testing the hypothesis that students combine online platforms differently depending on the availability of resources (H1).

RQ2: How does such use of the Web varies in relation to the curriculum? This question is answered by testing the hypothesis on whether students use different combinations of platforms over time depending on the proximity of curriculum-based tasks (H2).

## 2 Conceptual Framework

The study takes a departure point in sociomaterial theories of learning and builds on the notion of *activity* to conceptualize students' use of platforms. Activities are actions (or sets of actions) that do not exist in isolation, are directed towards objects and are bound to specific situations and circumstances taking place over time [6]. The study focuses specifically on activities involving the use of online platforms through the Web that support students' learning during their studies. Such activities are operationalized by building on two main constructs. First, *actions performed*, which are represented by events in which students access specific platforms. Second, *situations and circumstances* of those events, represented by curriculum-based tasks that students partake of during those same events.

## 3 Methodology

The study involved the voluntary participation of 73 CSE students, 33 in the fall 2020 and 40 in the spring 2021, invited through course teachers, and collecting three main types of data. First, students' self-reports on domain-specific activities performed while working in software projects or learning about software development methods, and the online platforms used to carry them out. Second, three-months of web-browsing history data of each one of the reported platforms was collected, consisting of the exact time and date in which the platforms were accessed. Third, documents from those courses students enrolled in during each corresponding semester with information about their different tasks and dates. Both self-reports and web-browsing history data were collected using a custom-made Google Chrome Extension, while the course documents are publicly available on the Web.

The dataset was prepared and analyzed in two stages using a quantitate ethnographic approach, in the sense that quantitative methods are used to make meaning of digital traces, in combination with self-reported and documents data. Stage 1 involved multiple methods. First, each one of the platforms was visited to perform a descriptive mapping of available technologies and was associated to domain-specific learning activities based on the self-reported data. The platforms were grouped into distinct types of platforms based on the results of the descriptive mapping. Second, the events in the web-browsing history data were grouped into smaller aggregated units (i.e., sessionization) by defining a maximum separation between events or threshold [7]. This threshold was defined by fitting a zero-inflated Poisson distribution over the counts of the separation in minutes between events. This resulted in 12,799 sessions, characterized by the types of platforms used, the frequency of access to each one of them and their duration in minutes. A subset of 3,336 sessions was selected for analysis based on learning activities associated to the types of platforms used, to increase the likelihood of the sessions being related to learning software development or working in software projects. These sessions were analyzed by performing a latent class analysis (LCA) with distal outcomes [8] in order to test H1. The LCA used the types of platforms accessed during the sessions (actions performed) as main variable, and the duration and frequencies of access as distal outcomes. Each one of the resulting latent classes was related to specific activities based on the self-reported data. Stage 2 involved building a secondary dataset to perform a latent profile analysis (LPA) of the weeks observed, used to test H2. The dataset consists of information about the (approximated) duration in minutes of each latent class for each week of the three-month period, representing different activities, and the curriculum-based activities taking place during those same weeks for each student. The LPA uses the duration of each identified activity, the proximity in weeks to each curriculum-based tasks and students' demographics as main variables.

## 4 Preliminary Findings

The LCA resulted in a five-class model being chosen after following the minimum BIC criteria, with an entropy of 0.906 that suggests good class assignment. These latent classes are characterized by distinct combinations of types of platforms being used based on the conditional probabilities of each latent class. Latent class 1 was characterized by the use of tutorials and courses platforms (e.g., W3Schools), and search engine platforms (e.g., Google). Latent class 2 by the use of questions and answers (e.g., Stack Overflow) and search engine platforms. Latent class 3 was characterized by the use of text libraries (e.g., Wikipedia) and search engine platforms. Latent class 4 mainly by the use of communication (e.g., Discord) and social networking platforms (e.g., Twitter), but also by video repository platforms (e.g., YouTube). Latent class 5 was characterized by the use of source code repository platforms (e.g., GitHub). The LCA also showed that the latent class also resulted to be significantly different in terms of the chosen distal outcomes (see Fig. 1). Moreover, preliminary graphical analysis of the secondary dataset suggests that important differences might be observable across the semester timeline for each latent class (H2), which are to be tested with the LPA.

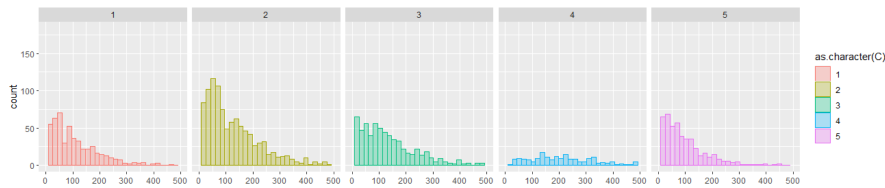


**Fig. 1.** Histogram for the duration of the sessions in minutes in each latent class.

## 5 Expected Findings and Contributions

With respect to RQ1, the presented findings corroborate H1, revealing clear patterns in the way students navigate the Web to learn software development. These patterns are associated to different learning activities and show that students access several different platforms and types of platforms using the Web while engaging in such activities.

With respect to RQ2, preliminary exploration of the dataset reveals important differences in the use of the Web across the semester based on the identified activities. It is expected that these differences will be significant when contrasted with events in the academic calendar (e.g., lectures and/or exams) once the LPA is performed.

This study's contribution is twofold. First, it provides empirical evidence of students' use of the Web and the online platforms accessible through it to support informal learning activities that are relevant for curriculum-based tasks. Second, it contributes methodologically, by showing how digital traces from the Web (i.e., web-browsing history) can be analyzed in combination with other types of data to generate valuable insights into learning processes that occur beyond curricular boundaries.

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# Learning Natural Selection through Computational Models in a High School A.P. Biology Classroom

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**Abstract.** Science education communities increasingly recognize the importance of computational thinking but lack empirically tested learning materials. We report the implementation of a computationally driven natural selection unit in an A.P. high school biology classroom. Data from 35 students at a large, Midwestern U.S. public school are analyzed via epistemic network analyses. Epistemic networks indicate that computational tools elicited different natural selection concepts from student responses. We interpret these results to show that attention should be given to the fit between computational tools and natural selection concepts.

**Keywords:** Computational Thinking, Natural Selection, Epistemic Network Analysis.

## 1 Introduction

Computational tools and methods have restructured scientific work. In response to this paradigm shift, computational thinking (CT) has surfaced as a national and scholarly interest. Due to CT's relative novelty, much of the research on CT has focused on the design of standards and curricular frameworks. Less attention has focused on empirically testing learning materials and exploring CT's ability to promote K-12 science learning [1].

In this poster we report the implementation of a computationally driven unit to address these gaps. We extend from previous work involving students' computational modeling of evolutionary processes to address the well-established and considerable difficulties students have in learning natural selection [2]. Students in this study (N=35) interacted with four computational tools across an 8 week, 7-lesson unit on natural selection in an A.P. high school biology classroom within a large public school in the U.S. Midwest. We report two tools below in Figure 1: A computational model of natural selection developed in NetLogo and in Figure 2: an interactive data environment about Galapagos finches developed in the Common Online Data Analysis Platform [3].

The following research question guided our work: "How do computational tools facilitate learning of natural selection concepts?" We center epistemic network analyses in this study to better identify and understand the shifts in student reasoning about natural selection that occur within and between lessons, and to provide empirical support of computationally driven natural selection curricula. In the Rock Pocket Mice model (see Fig. 1), students experiment with parameters such as initial variation, environment color, presence and rate of predation, and may intro duce mutations into the population.

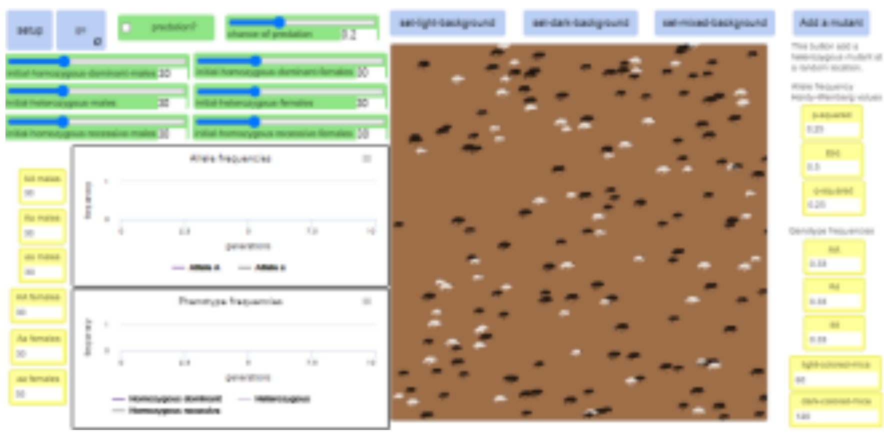

**Fig. 2.** NetLogo model from Lesson 4: Natural selection of rock pocket mice.

In the CODAP model (see Fig. 2), students visualize and analyze a database of Galapagos Finch traits such as beak length, depth, and width, weight, wingspan, and sex.

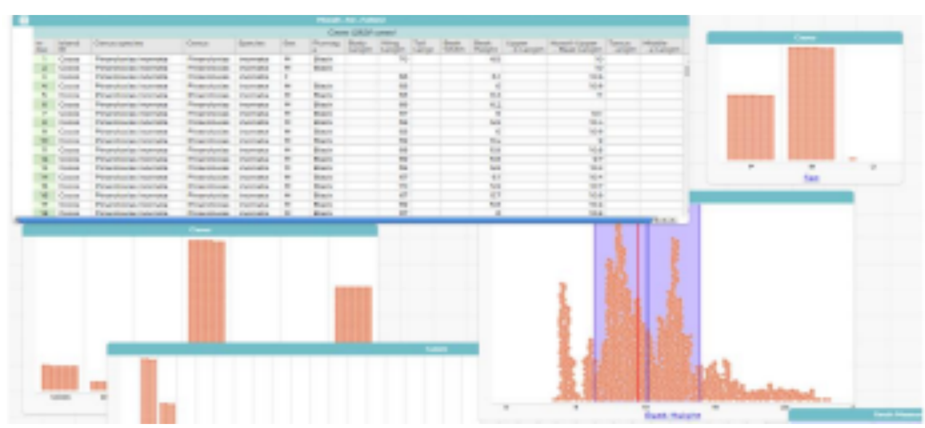

**Fig. 2.** CODAP model from Lesson 6: Galapagos finch data.

## 2 Methods

We analyzed student responses to two summative assessment questions embedded in the unit that correspond to two different computational tools and therefore distinct opportunities to investigate the influence of computational tools on student reasoning. Three researchers used a previously developed coding guide to code unit questions and student responses. Interrater reliability was high across all codes (K = 0.91). We conducted epistemic network analyses [4] to understand (1) student use of natural selection in reasoning about speciation and (2) the effect of computational tools on student use of natural selection concepts.

## 3 Results

We highlight one student's responses to the summative questions to situate the epistemic network analyses that follow. See Student A's labels below in Figure 3.

> I learned that natural selection is the process by which organisms better adapted to their environment tend to survive and produce more offspring. I also learned that natural selection is caused by environmental changes that chooses a desired trait. (Student A; CODAP) Finches from the mainland travel to an island, but were separated into 2 groups because of continental drift breaking apart the island. One island had large seeds, so the finches evolved to have big beaks and reproduced. On another island, small seeds were found so the finches evolved to have small beaks. These two groups created 2 new species. This happened with several characteristics (Student A; NetLogo).

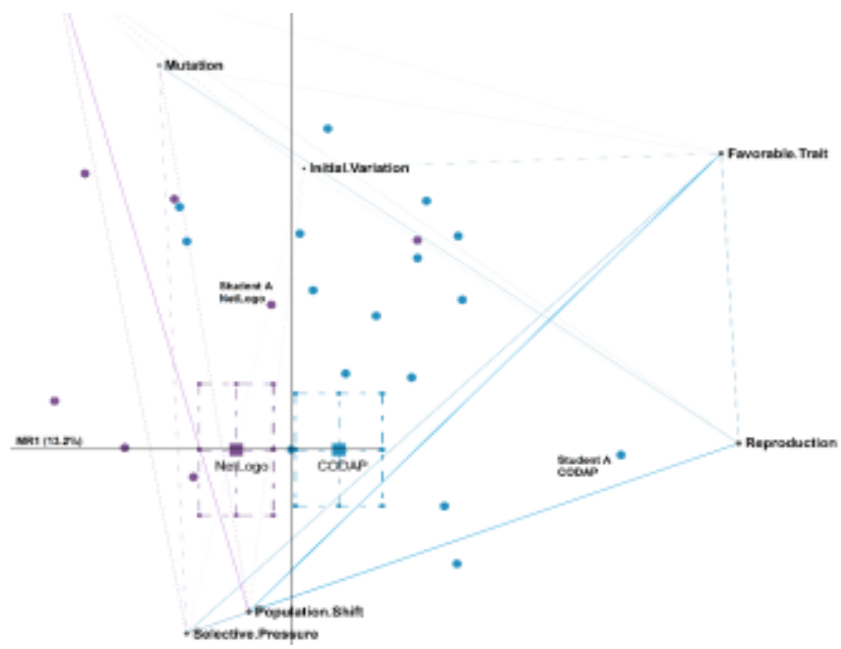

**Fig. 3.** CODAP model from Lesson 6: Galapagos finch data. Comparative epistemic network graph of student use of natural selection concepts follows NetLogo (purple) and CODAP (blue) model use.

Figure three shows a subtractive, comparative epistemic network of students' use of natural selection concepts in their summative responses to the lesson with NetLogo (Purple) and CODAP (Blue). The structures of the two networks represent differences between concept co-occurrences. For example, responses following the NetLogo model included differential survival, selective pressure, and population shift, but rarely reproduction. Line thickness indicates relative frequency of co-occurrences between students' use of natural selection concepts in their responses. One finding is that students used population shift after both models, but more frequently after the CODAP lesson, indicated by the bolder blue and fainter purple lines from the node.

## 4 Discussion

Analyses indicate that computational tools can facilitate learning of natural selection, and to varying degrees. For example, in the lesson with NetLogo students used selective pressure and population shift concepts to explain natural selection in rock pocket mice, but fewer of the five remaining concepts (see Fig. 3). Students then applied knowledge of natural selection to explain speciation of finches in the Galapagos and exhibited greater knowledge of favorable traits and reproduction (see Fig. 3). We suspect this difference reflects the foregrounding of favorable traits and reproduction in the CODAP environment, which indicates that the explicitness of natural selection concepts in tools may lead to differential learning outcomes. Comparative epistemic network analyses further support this interpretation and show that the NetLogo model elicited greater cooccurrences between differential survival, selective pressure, and population shift, key design principles of the model. On the other hand, student reasoning relied more on reproduction and favorable traits in the CODAP environment. Both tools surfaced initial variation, and mutation concepts to lesser degrees, corroborating prior challenges found in teaching evolution [2]. Taken together, these results indicate that future work should investigate the fit between computational tools and natural selection concepts so that designs may better facilitate student learning.

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# Making Sense of Teachers' Communities of Practice with Epistemic Network Analysis

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**Abstract.** Community of Practice has been described as a set of relations emergent through shared practice and commitment to a professional goal and it became a popular framework for researching social learning and professional development amongst teachers. To date, studies of teachers' communities of practice (CoP) have focused on single dimensions of situated learning and its effects on professional agency. However, there is a significant gap in the empirical research about the role of agentic behaviors and contexts of practice on the dynamics within a CoP. This study is an exploratory study of teachers who identified and worked jointly to address the professional goals of their practice. We used ENA methods to map interactions between teachers in a rural teacher community in Scotland in the UK. The data were collected and analyzed using a quantitative ethnographic approach -- a mixed-methods network approach to narrative data. The results illustrate the potential usefulness of epistemic network visualizations for mapping and comparing teacher communities across different contexts of their practice.

**Keywords:** Teacher, Community of Practice, Relational Agency.

## 1 Introduction

Teachers' Communities of Practice (TCoP henceforth) has been promoted on the grounds of its benefits to students learning outcomes and as a professional learning tool that is effective in encouraging innovation [1]. There is overwhelming evidence suggesting the positive impact of TCoP on professional identity and beliefs [2], stocks of collective knowledge [3]and teachers' experience. TCoPs have been extensively researched with a focus on the specific contexts of practice, such as inadequacies of school structures [4]; as a strategy to popularize changes to practice [5]; or implement policies [6] with a predominant focus on measuring the effects on individual actions within the TCoP [7]. Few studies have looked at the internal dynamics of a CoP but have mainly focused on the effects on the individual professional agency as well as professional identity and learning [8]. There is a gap in empirical evidence that would consider agency as the key dynamic within a TCoP e.g., how teachers work together across different contexts of practice; and how they come to negotiate and exercise their work through agentic behaviors including reaching out to other people and locating resources to help them find solutions to problems in their practice [4].

In this study, we aimed to explore this through a lens of relational agency, defined *as a capacity to engage with others to interpret and act on the object of actions* [9]. We were interested in the kind of interactions teachers sought within and outside of their school setting to address their professional goals, and how these interactions contributed to those goals. We collected the data from a whole-school TCoP where teachers worked jointly to address their professional goals at work. We used Epistemic Network analysis as an early attempt to visualize this TCoP based on professional goals and types of interactions and their content that occurred in the school.

## 2 Method

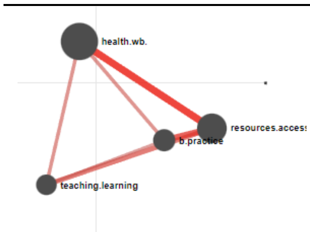
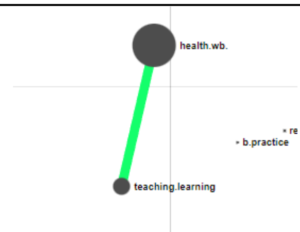
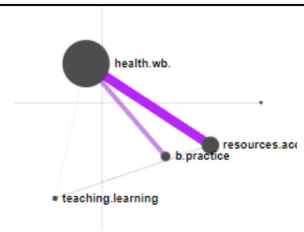
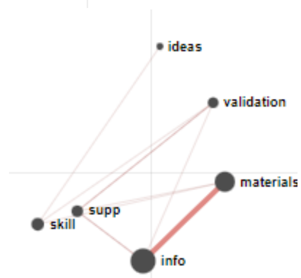
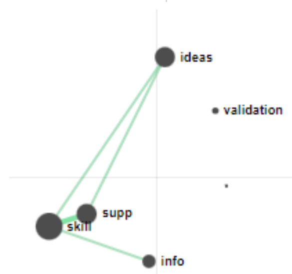
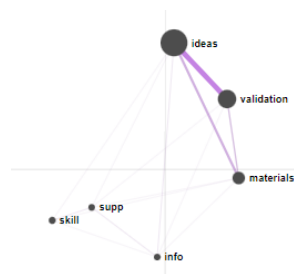
The data was collected in 3 waves between January and April 2021 in a small rural school in Scotland (n = 10 teaching staff including the head teacher and learning assistants) using previously validated qualitative survey measure in another research of teacher agency [10]. The survey included social network items i.e., teachers nominated who they interacted with for what goal and rated the interaction from communication as the simple form of interaction, advice seeking/giving, and collaboration as the more complex form of interaction based on joint decision making. Teachers also filled out open-ended responses (why the person became involved, their contribution and the overall outcome of the goal). There were 9 survey responses in total (from 7 respondents). Each entry contained rows of data with the goal, alter's initials, reflection, alter's role, type of interaction, reasons for the involvement of that alter and the contribution of that alter. In total respondents logged several interactions totaling 72 cases of interactions.

We defined the units of analysis as all lines of data associated with a single value of interaction subsetted by alter (teacher, headteacher, parent etc.). We coded the individual goal of interactions (e.g. looking for a lesson plan, helping to organize a school event, calming down a student) as aggregate codes for goals e.g. looking for a lesson plan as *teaching and learning continuity* (maintaining a learning process and delivery of teaching); administering medication to a student as *health and well-being of students*; designing new outdoor activities as *best practice* (searching for methods to enhance students learning); and *locating and accessing resources* (tapping into stocks of knowledge of other teachers, stakeholders or experts). From the section 'how did the person contribute to the goal' we developed codes for the types of contributions: information; ideas; materials (e.g., plans, books, testing kits); skill; support (with plan and strategy) and validation (approval from a colleague of choices and ideas).

## 3 Results

Our model had co-registration correlations of 0.96 (Pearson) and 0.95 (Spearman) for the first dimension and co-registration correlations of 0.97 (Pearson) and 0.97 (Spearman) for the second. These measures indicate that there is a strong goodness of fit. In terms of types of individual interactions and contributions along the Y axis, a two-sample t-test showed COMMUNICATION (mean=-0.48, SD=0.70, N=9 was statistically significantly different at the alpha=0.05 level from COLLABORATION (mean=0.55, SD=0.76, N=6; t(10.29)= -2.67, p=0.02, Cohen's d=1.43) but there was no statistical difference between other types of interactions. Collaboration was more common between school staff and external stakeholders (e.g. specialist subject teachers, health workers, and parents). Communication was present across all of the goals with the most common contributions as information and materials. Collaboration occurred when teachers wanted to address students' health and well-being, locating and accessing resources and when looking to enhance students' learning (best practice) with the contribution of materials as well as validation of choices and ideas.

**Table 2.** Interactions occurring across different goals and types of contributions per each interaction.

| Communication | Advice | Collaboration |
|---|---|---|
|  |  |  |
|  |  |  |

### 3.1 Conclusions, Limitations and Next Steps

These findings suggest the potential of using the ENA model to map the intentional behaviors of teachers to reach professional goals in their work. However, our study is preliminary, our data contained a small sample, and these findings and insights should not be generalizable to other settings. Future studies could make use of the methodology on already existing or new larger conversational and interaction data to show whether these differences are significant and generalizable. Our study, although longitudinal in the planning stage (3 waves), suffered from inconsistency because of the Covid-19 pandemic and the difficulty to obtain responses from teachers. Thus our data became a snapshot of reality. Future studies could benefit from including longitudinal analysis as we see the potential of ENA to map interactions across different goals and time.

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# Leaving Ukraine: Analysis of Interviews with Ukrainian Refugee Women on Lived Escape Experiences

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**Abstract.** This brief study examines reflective interviews conducted by *The New York Times* of four women who left Ukraine shortly after Russia's invasion on February 24, 2022. ENA was used to model the discourse patterns to identify the most relevant connected constructs that emerged, to understand how the women were reflecting on the chaotic experience. The most prominent connections created a triangle between Lack of Resources, Escape Scenario, and Destruction, indicating the strongest reflections involved describing how the destruction in the area led to a lack of resources, which prompted the need to escape. While these connections were most prominent, another prominently connected construct was Community, indicating the importance of assisting each other when possible. These reflections provide a snapshot of immediate experiences in a time of conflict.

**Keywords:** Ukraine, war in Ukraine, Russian invasion, refugees, women, crisis, lived experiences

## 1 Introduction

In times of crisis, individuals' perceptions and realities can be profoundly affected [1]. Affected individuals often subsume, process, and act on feelings differently than during a non-crisis time. For example, individuals may adjust their communication responses by holding on to current belief systems in an attempt to navigate within new systems and new ways of life [2]. One such crisis was witnessed on February 24, 2022 when Russian military forces entered onto Ukrainian territory.

The study explores the impact of this crisis on four Ukrainian women, sourced from *The New York Times*. Interviews from these Ukrainians were analyzed to examine emerging connections during a time of crisis in war utilizing Epistemic Network Analysis (ENA). ENA examined the patterns and discourse of connections between shared themes in citizen and refugee stories based on their perceptions of the war on Ukraine.

## 2 Methods

This study examines the escape stories of four female Ukrainian refugees, seen in Table 1. These stories were sourced from an article published on March 20, 2022 in *The New York Times* by a reporter who interviewed refugee women approximately three weeks after the war began [3]. The reporter acknowledged that the stories were edited and condensed for publication.

**Table 1.** Description of participants and interview dates.

| Participant | Age | City of Origin | Interview Date |
|---|---|---|---|
| Vika K. | 46 | Bucha | March 12, 2022 |
| Darian P. | 37 | Mariupol | March 11, 2022 |
| Alyona Z. | 33 | Irpin | March 10, 2022 |
| Maria N. | 36 | Andriyivka | March 15, 2022 |

A codebook was developed through three iterations of a grounded analysis of the data by six researchers, seen in Table 2. Once the codebook was developed, each sentence in the four escape stories was coded by two raters, following a process of social moderation to reach agreement on the final coding decision. ENA was used to examine the pattern of connections between shared themes in the refugees' stories. For this analysis, a sentence was defined as the unit of analysis and the four separate refugee stories were defined as the conversations. The moving stanza window was set to seven and a minimum edge weight of .01 scaled to 1.8 was applied to highlight the most prominent connections in the data.

**Table 2.** Codebook of constructs used in analysis.

| Type | Definition |
|---|---|
| Community | Helping others, assisting, care for those left behind, relationships (includes both actions and thoughts) |
| Defend | Fighting back, resistance, standing their ground, nationalism |
| Destruction | Negative action/observations/danger towards objects (e.g., bombing, sounds) |
| Disbelief | Feelings related to disbelief (e.g., surreal, like a dream, sense of time, etc.) |
| Escape Scenario | Related to evacuation, hiding, fleeing, survival as well as challenges encountered with the escape process (e.g., blockades, not being able to evacuate due to gender, etc.) |
| Lack of Resources | Describing lack of resources (e.g., supplies, communication, infrastructure, etc. |
| Normalcy | Sense of "normal life," normality or comparison to how things were |
| Negative Affect | Feelings related to negative emotions (e.g., anxiety, guilt, fear, longing) |

| | |
|---|---|
| Positive Affect | Feelings related to positive emotions (e.g., gratitude, hope) |
| Protect | Protecting the vulnerable (e.g., children) |
| Violence | Negative action/observations/danger towards people (includes mention of shooting, which can be aimed at a person) |
| Visceral Response | Describing personal bodily, physical response/reaction that is not an explicit emotion |

## 3 Results and Discussion

An ENA model reflective of all four interviews is presented below in Figure 1. The X axis of the model is defined by Community on the left, and Escape Scenario on the right. The Y axis of the model is defined by Lack of Resources at the top and Violence and Destruction at the bottom. The large thickness of the line connecting Escape Scenario and Destruction indicates the strongest connection within the model. This implies that much of the reflection emphasized the negative action/observations/danger towards objects they encountered while escaping. Qualitative examples made it clear that destruction was a driving factor for escaping their homes. When interviewed, Daria P. stated, “So, we got gathered all together, a huge column of lots of our friends and people we knew. There’s a lot of shelling, but we still decided we should try to drive.” In this statement, Daria mentions escaping their town while the destruction of shelling is happening around them.

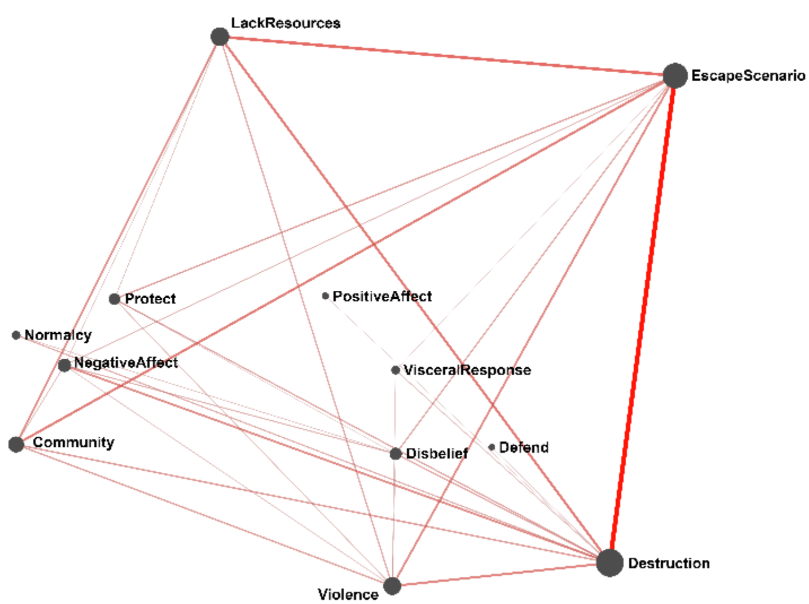


**Fig. 3.** ENA model of interviews with four Ukrainian women.

In the model, there is also a prominent triangle between Lack of Resources, Escape Scenario, and Destruction. This aligns with participants conveying how the destruction in the community led to a lack of resources, which prompted the need to escape. In the interview, Vika K. commented, “But they didn’t have medicine. They couldn’t call an ambulance because there was none. I honestly don’t know about his fate. I just had a feeling that we had to get out of there. Every minute you hear these explosions, these shots somewhere nearby, it’s hard to understand, are you a target?” Here Vika K. states how there was a lack of resources such as medicine and ambulatory care, while shots and explosions are nearby, thus having a feeling to escape the situation.

The aim of this analysis is to examine the very initial raw reflections of Ukrainian women shortly after the Russian invasion. ENA helped to determine the connections and relationships between constructs that emerged from the interviews, which gave an immediate insight into the situation. The model reflects how the early onset of the invasion had an influence on how the interviewees responded to the initial questions from the reporter. One of the limitations of the study is that the data only represents the edited interviews in the final article, so the researchers did not have access to the original raw data. Another limitation is the small number of interviewees; hence a sentence was used as the unit of analysis. Despite the small dataset, this still provided a snapshot of the time sensitive insights of Ukrainians on the changing situation at the time. Opportunities for future study include a wider dataset with more responses at the conclusion of the crisis to draw more conclusions on how the impact of the war in Ukraine affects particular subgroups, including women.

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# Choosing STEM: How Underrepresented Students Make Major and Career Decisions

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**Abstract.** Given the unbalanced representation of graduates in different STEM job segments, there is a need to explore how students from underrepresented backgrounds arrive at their STEM major and career decisions. By conceptualizing this process as part of students' identity exploration, this work examines conceptual connections between identity-related themes made by student participants of a federally funded STEM minority participation program as they reflected on major and/or career choices. Findings showcase STEM identity exploration as a developmental process, as students frequently associate past interests and choices as impacting current interests, values, and actions. Interpretive findings reveal the more universal motivational factors that influence career and major choice, as well as students "taking action" by engaging in institution-supported STEM activities. External influences such as family and community were also described as impactful. This work helps to inform the design of STEM minority participation programs to support major and career choices.

**Keywords:** STEM Minority Participation, STEM Major and Career, Identity Exploration, Epistemic Network Analysis

## 1 Introduction

STEM workforce shortages remain a concern in the United States. Recent reports on the STEM workforce reveal both shortages and surpluses of STEM workers depending on the job segment [1]. Further, despite overall STEM workforce growth in recent years, Blacks, Hispanics, and women remain underrepresented in some STEM jobs such as computing. There is a need to explore how college students engage in major and career decision-making in STEM, particularly among underrepresented minority (URM) students, so that targeted efforts can be directed to diversify STEM participation and expand the STEM workforce in needed fields.

Studies have found students' exposure to STEM as significantly contributing to STEM major and career choices. These exposures are mostly activity-based, such as enrolling in courses, internships, and STEM competitions [2]. Student decision-making around STEM majors and careers can also be influenced by important others, such as parents, teachers, peers, and mentors [3]. In addition to external factors, internal factors related to motivation such as interest, valuing, and self-efficacy have been widely cited as key to STEM participation [4].

We frame STEM major and career choices as part of a learner's long-term trajectory of *identity exploration*, influenced by the aforementioned external and internal factors. Identity exploration is a developmental process that holistically encompasses cognitive, affective, and behavioral features of the *self*, as well as self-definitions and self-perceptions [5]. Post-secondary initiatives that support such processes are likely to yield positive results in encouraging UMR students to declare majors and seek out careers in STEM. While qualitative and mixed-methods studies exist featuring interview data [6], few quantitative ethnographic (QE) [7] works elucidate the complex interconnections between identity-related factors as URM students engage with STEM at the college level. This work aims to understand such processes using QE in the context of a federally funded STEM minority participation program. The research question asks, "How do URM college students conceptualize their STEM major and career choices as part of their long-term identity exploration?"

## 2 Methods

This study is part of a larger NSF-funded research initiative, the Louis Stokes Alliance for Minority Participation (LSAMP) in the Greater Philadelphia area, which supports URM students in STEM through various initiatives. Twelve student participants volunteered for a virtual interview, representing five LSAMP institutions and nine STEM disciplines. To specifically explore how students conceptualized their major and career choices, a sample dataset was generated consisting of responses to questions such as "What made you choose this STEM topic?"

This work leveraged a hybrid approach of coding involving both data-driven and theory-driven codes. The authors first independently derived themes using an inductive approach and then discussed to reach a consensus on a coding scheme (see Table 1) informed by identity exploration and literature on major and career choices.

**Table 3.** Codes related to LSAMP participants' major and career choices in STEM

| Code | Exemplary quote |
|---|---|
| Community & Society | "So that I can help build roads and fix under-developed rivers." |
| Family & Friends | "With my father being an engineer and teaching engineering…" |
| Interest | "I took a Computer-aided Design class and I really enjoyed that." |
| Knowledge & Skills | "A seminar class that we do research gives me the tangible skills." |
| Mentors | "My biology teacher inspired me to be a bio major." |
| Roles | "I plan to go to med school to be a pediatric surgeon." |
| Role Models | "I started out in electrical because a guy from Boeing was there." |
| Self-Efficacy | "I really started to learn code and got somewhat good at it." |
| Taking actions | "I was in that (high school competition) as a software lead… |
| Topics/ Fields | "Whereas for mechanical engineering, we touch-base on…" |

| | |
|---|---|
| Valuing | "Biochemistry becomes important because I know every single thing that is going into my food." |

Once a coding scheme was established, each line of responses was coded for the occurrence (1) or non-occurrence (0) of each code listed above and the timeline codes. Interrater agreement was reached using social moderation. Epistemic network analysis (ENA) was applied to the binary-coded lines. The units of analysis were set as interviewees in the sample (N=12). Conversations were segmented by interviewee and any breaks in interviews. ENA findings are supplemented with qualitative findings.

## 3 Results and Discussion

The network model had co-registration correlations of 1.00 across the x and y-axis, indicating strong goodness of fit. Figure 1 shows the three timeline codes ("past", "present", "future") were relatively highly connected. The discourse was mainly driven by discussions of the "past," "present," and "topics/fields". Relatively robust associations also manifested between discussions of the "past" and "interest" (0.2), "present" and "valuing" (0.19), "past" and "taking action" (0.19), and "past" and "valuing" (0.18).

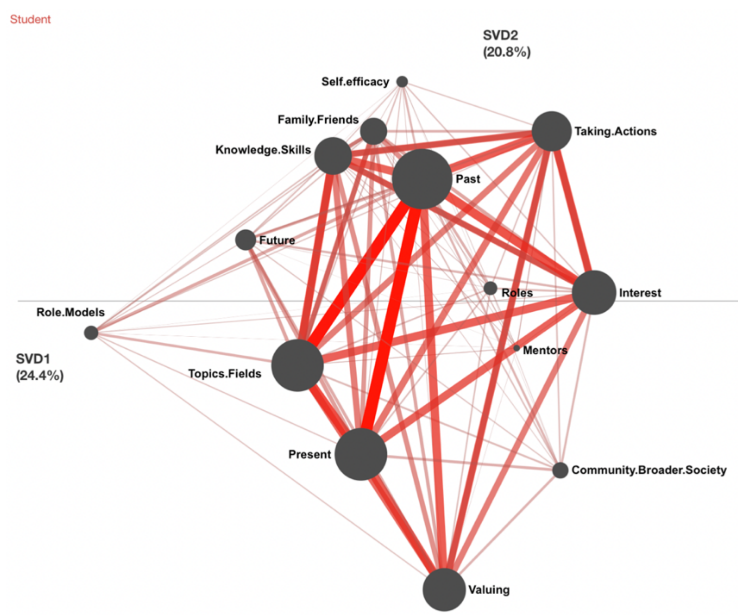


**Fig. 4.** Epistemic network of associations between identity themes

Interpretive examination confirms this rather consistent pattern. Students started by recalling their initial interest in a STEM topic, then through open-ended exploration reflected on the topic as it relates to them in the present (e.g., enjoyment, usefulness).

This often transitioned to discussions of increased certainty in their major/career decisions. This process was not necessarily linear. See the example below:

> I wanted to go down environmental engineering. (Past, Topics/Fields, Interest); But environmental engineering is a very specific area…you have very limited options. (Present, Topics/Fields); Whereas for mechanical engineering, we touch base on all disciplines of engineering. (Present, Topics/Fields, Valuing); Having a mechanical degree with an environmental (minor)…I have more options post-graduation. (Future, Topic/Field, Valuing).

While connections to external factors such as family and communities were sparser, we believe these codes were not necessarily less *impactful* but were less *universal* contributors to students' major and career decisions. For example, one participant shared, "[I picked molecular biology] because my family has type two diabetes."

## 4 Conclusion and Implications

This work aims to investigate conceptual patterns as undergraduate student participants of a STEM minority participation program reflected on their major and career choices in STEM. Findings highlight student identity exploration in STEM as a developmental process, as students frequently associate reflections of the past and the present with identity constructs. Students were universally likely to reference the internal affective features (e.g., enjoyment and usefulness) as well as the behavioral features (regulatory action-taking) of the *self* when engaging in active exploration of STEM majors and careers [4, 8]. External constructs such as family/friends and societal causes were sparsely connected but meaningful to some individuals.

Findings shed light on the need for STEM participation programming to support students' exploration of different STEM topics through adequate discipline-related information and activities. Programming should be intentionally designed with the goal of promoting internal motivational aspects such as interest and values students associate with specific STEM disciplines in demand. Furthermore, this work demonstrates the utility of QE techniques for visualizing identity exploration among STEM students.

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# Studying the Development of Computational Thinking and Gender through Epistemic Network Analysis

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**Abstract.** Underrepresentation of women in the STEM fields is of national concern. However, recent research has concluded that females and males are performing similarly when it comes to testing and assessing the ability to perform in STEM related subjects or tasks. Thus, we propose a study to explore if an all-boys student team elicits similar or distinct components of computational thinking when compared to an all-girls student team, when both teams are asked to solve a model-eliciting activity (MEA) to create a model for a computer algorithm. We used Situated Expectancy Value Theory as an interpretative framework and Epistemic Network Analysis as an analytic tool to help us understand how each team elicits computational thinking within their context and situation. We conclude that both teams successfully developed a model for the computer algorithm. However, ENA was able to illustrate those characteristics of computational thinking that each team more strongly emphasized in the process of solving the MEA.

**Keywords:** Computational Thinking, Model-eliciting activities, Gender, Situated Expectancy Value Theory, Epistemic Network Analysis.

## 1 Purpose of the Study and Research Question

The need for STEM professionals has been growing steadily, the shortage in the workforce is expected to reach 1.5 unfilled positions by the year 2023 in cybersecurity alone [1]. Despite efforts in outreach and education, women still have lower representation with less than 20% of female students in high school declaring a STEM major [2]. To better understand female participation in STEM, we propose a study to explore if a team of all-girl students elicits computational thinking in similar or distinct ways when compared to an all-boy team of students solving the TicTacToe model-eliciting activity (MEA) [3]. Results will help us better understand how students' gender might play a role in how boys and girls create their own meaningful understanding of computational thinking when engaged in MEAs as a learning environment.

The research question for this study is: What are the similarities and differences in the ways in which two teams composed by all-boy and all-girl students, respectively, develop ideas of computational thinking (CT) when solving a model-eliciting activity?

## 2 Theoretical Framework

Situated Expectancy-Value Theory (SEVT) studies the psychological and contextual factors that mark gender differences in STEM [4-5]. According to SEVT, students put effort in activities that have value for them and those at which they are expected to succeed. For this study, we analyze gender through Utility STV, or how a task helps students in present and future plans and goals. While working in an active learning environment, students choose how to engage with the subject they are learning, they then decide the amount of work they will do to maximize their experience. Having the choice on how to engage makes the activities more purposeful, Thus, we focus mainly on the Utility STV and how it might be different for two teams, one all-girls and one all-boys, as they engage in a task where the short-term goal was to elicit CT.

Computational thinking is a set of mental tools that reflect critical concepts in computer science [6]. We operationalized CT using four skills [7] (a) decomposition: breaking problems down into smaller parts, (b) pattern recognition: finding similarities between items, (c) abstraction: removing details for generalization, and (d) algorithm: automating the processes by designing a sequence of logical instructions.

Model-eliciting activities (MEAs) include explanatory systems that function as models in which students interpret problem-solving situations. From a Models and Modeling Perspective (M&M), MEAs have been used as curricular activities in STEM education [8-9]. MEAs engage students in a process to come up with a model as a solution to a specific problem posed by a client. MEAs help students develop problem solving skills, along with prediction, decision-making and communication skills [10]. MEAs are symbolic descriptions of meaningful situations that give teachers the opportunity to guide their students through the process of learning [8, 11].

We build on previous findings from Carmona, Galarza & Martinez [12] and extend our findings to use SEVT to analyze how the TicTacToe MEA can provide a purposeful and meaningful context for girls and boys to develop CT.

## 3 Methods

Discourse analysis studies patterns in speakers and listeners, which can be used to infer significant trends. It can be studied in a pragmatic way, learning about the contextuality of specific meanings or it can be the study of "texts" as a whole, and how sentences and utterances can give meaning across patterns [13]. It can help analyze the conversations of the students throughout their learning process of CT. This is consistent with M&M approaches since the process of creating the model is the product [12].

Quantitative ethnography uses statistical techniques to increase the scope and power of ethnographic or other qualitative methods [14]. It models the association between elements of complex thinking. Epistemic Network Analysis (ENA) models cognitive networks, using visualization and statistical techniques to identify patterns and quantifying the co-occurrence of concepts within a conversation [15].

ENA analyzes data segmented, based on the principles of discourse analysis, starting with lines and grouping the conversations in stanzas or whole activities. Relationships are calculated and depicted graphically looking at the co-occurrences of concepts in the conversations [16]. ENA can construct a subtracted network that shows the differences between two networks by subtracting the weight of the connections from two networks and highlighting the differences between two teams.

### 3.1 Participation Selection, Data Collection and Analysis

We purposefully selected two teams from two different high schools: one with three boys and one with three girls. The discourse of each team developing CT demonstrates their utility subjective task value (how their team conversation helped them come up with an algorithm). Each team was given the TicTacToe MEA designed for students to elicit CT. After students were introduced to the context of the activity by video or a newspaper article, each team asked to come up with a set of rules and a procedure to help a machine play tic-tac-toe with a human and win every time. Each team spent about 50 minutes solving this task.

The conversations in teams were be observed, audio, and video recorded, transcribed verbatim, double-coded and analyzed through the lens of discourse analysis. For a balanced coding related to gender, the coders were one man and one woman.

ENA allowed us to identify the different constructs each team elicited during the process of solving the MEA. The units analyzed were the teams. The conversation was the discussion each team had during the completion of the MEA. The unit measured was the intervention from each team member; every time the conversation shifted to a different team member, a different line or unit was created. The moving window stanza was set at 20 lines, considering that meaningful conversations may take more than the standard 4-window stanza.

## 4 Results and Interpretations

In order for us to enhance the understanding of the different conversations we plotted through ENA the conversations with co-occurrences of both teams. The first ENA plot (see Fig. 1) shows the space in which the two teams moved during the conversations. The red plot represents the three-boys team and the blue pot represent the three-girls team. Consistent to previous studies [12], the TicTacToe MEAs was a successful context for both teams to elicit CT in a meaningful and purposeful way. The fact that both teams successfully solved the MEA is consistent with the literature in that there are no differences in performance between boy and girl students in STEM [4]. However, Figures 2 and 3 evidence differences between the two teams, showing that each team elicited CT in ways that can be characterized differently (decomposition, patterns, abstract and algorithms). The Utility subjective task value was also different for each team, each one eliciting CT in their own context, giving value to their own different characteristics.

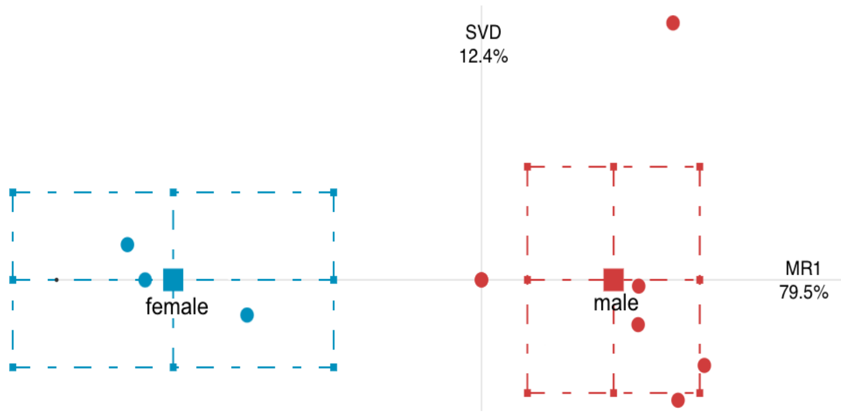


**Fig. 5.** Both teams' conversation.

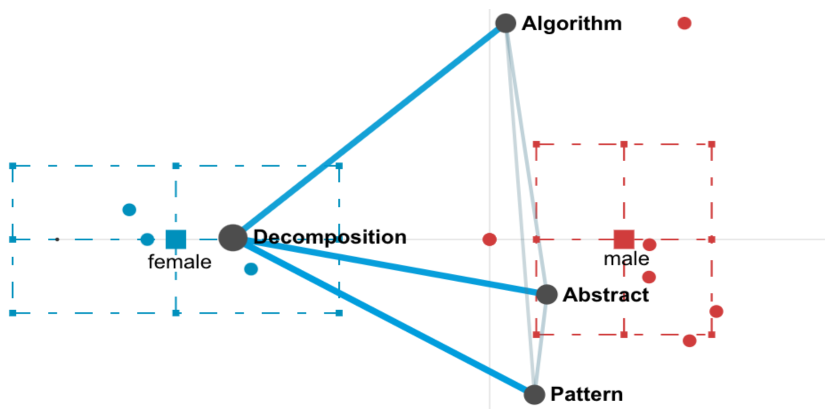


**Fig. 2.**

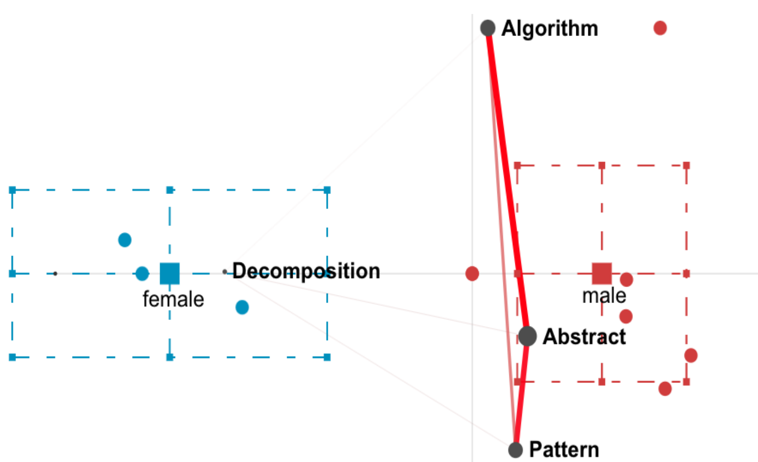

**Fig. 3.**

The ENA plots in Figures 2 and 3 show how the girls' team focused on decomposing the task and understanding the activity, as they identify parts of the problem and breaking it down to manage. Whereas the boys' team had discussions between concepts abstract-pattern, abstract-algorithm and with lower co-occurrence, algorithm-pattern. The all-boys team focused on generalizing the solution so they could work with a set of instructions for every time they played TicTacToe. ENA subtracted network in Figure 4 confirms that the all-girl group focused more on decomposition.

## 5 Conclusions and Next Steps

We used ENA to understand how two groups, one all-girls and one all-boys, elicit CT in successful ways, creating a solution that is purposeful and meaningful but in a different way for each team. A well-designed MEA gives all students the opportunity to include their "Cultural Milieu" and assign value to the activity, in consequence all teams have the expectation to succeed and are engaged in solving the problem. ENA allowed comparing conversations and discerning on which constructs were relevant and valuable for each team. The plots generated display the diversity in student thinking elicited by each team.

This study warrants further exploration on the how MEAs promote and encourage women to elicit CT, and how the way in which they elicit and understand CT might be similar or different to the way male students develop their thinking. For the purpose of this study, we focus on gender as a variable to analyze the development of two teams' CT. To address some limitation of this study, future research needs to be done on other parameters that also influence the learning and teaching of CT.

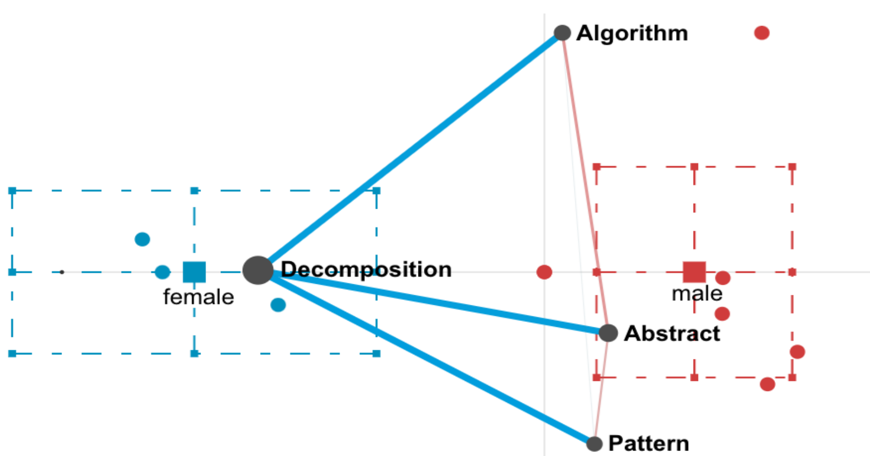


**Fig. 4.** Subtracted network.

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# Using Social Annotations for Knowledge Construction During Online Collaborative Text Study

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**Abstract.** Social annotations allow groups of learners to read and annotate a shared text collaboratively. In this study, we use social annotations as a prompt intended to facilitate close-reading of academic texts by allowing students to ask questions, make comments, or create a connection between the text and additional sources. Thus, social annotations nurture both individual and collaborative interaction with the text. Relying on Perusall, a social annotation platform, we examined students' knowledge construction activities during online collaborative text study. Using Epistemic Network Analysis, we compared the different connections participants made between various knowledge construction activities they performed. Our findings indicate that ENA can be used to identify and offer new typologies of student participation in social annotations.

**Keywords:** Social Annotations, Online Text Study, ENA.

## 1 Introduction

### 1.1 Online Collaborative Text Study

As students participate in dialogical verbal activities, they reflect, explain, and articulate their own thinking and reasoning. They may also clarify misunderstandings and challenge their views or those of others. During such participation, their cognition is shaped through social interaction, which includes efforts to improve their understanding of the subject matter. Beyond these affordances of verbal communication, textual computer-mediated communication can establish productive argumentation as learners reread and revise their comments before and after they post them, allowing them to reflect on their work. In addition, in such settings, students are more likely to share their personal views as the social presence of others plays a less dominant role [1].

### 1.2 Social Annotations

A comment is one kind of text that is reactive, short, and asynchronous [2]. Annotations are usually informal and unstructured comments written in the margins of a text. They may include a question regarding the text, a correction, explanation, interpretation, and more. Annotations can also include agreement or disagreement with the author, marking important information, or answering questions. In addition, annotations can include drawings or links to additional texts [3]. In this regard, annotations can be viewed as the reader's way of talking to or with the text.

Kalir and Garcia [2] demonstrate how previous interdisciplinary research has shown that annotation, whether written by hand or in a digital format, assists learners in thinking, reading, and writing and often bolsters their motivation for learning. Today, annotations can be digital as part of online annotation systems, enabling users to share their annotations, rendering this individual process a collaborative endeavor.

Social annotations in educational assignments have been referred to by scholars as *anchored discussions* in which students “talk” about a shared text through digital annotations. As Kalir and Garcia [2] claim, annotations enable a rich conversation requiring students to actively read the text and use the social annotations to elaborate their thoughts and learn from other perspectives through different interpretations of the text. Studies have also shown that annotating becomes a social act when shared annotations are visible, and students are more likely to become peer instructors and learners [4].

## 2 Methods (Data Collection and Analysis)

Participants (n=12, 83% female, 17% male) were students in an undergraduate education course. As part of this course, students participated in two asynchronous reading tasks. In groups of six, they annotated a shared text using Perusall, a platform designed to allow students to share annotations and respond to each other's comments.

To study and quantify the knowledge construction activities both on an individual and a collective level, we analyzed 271 annotations. The coding of each annotation included its knowledge construction activity based on the codebook developed by Morales et al. [5] (see Table 1). We then utilized the epistemic network analysis (ENA) tool to better understand the relations between students’ different knowledge construction activities. ENA enables researchers to model the structure of connections between and across codes based on discourse. Such a network includes links between codes and the strength of the connection [6]. We divided the text according to threads (annotations and their second-level comments). Each thread can be viewed as a short discussion within the broader group of students’ social annotations.

**Table 1.** Knowledge construction activities.

| Code | Definition | Example |
|---|---|---|
| Conflict | Disagreeing with another student; mentioning a different point of view in direct reply. | “It is true that knowledge can be a sign of social status but I do not agree that this is usually the case […].” |
| Consensus building | Discussion of misunderstandings; reaching an agreement on an idea, fact, or interpretation; | “In my opinion, it is possible to design the school in such a way that it will be |

| | | |
|---|---|---|
| | negotiating the definition, interpretation, or truthfulness of a claim or fact. | relevant by changing our views and redefining its purpose.” |
| Elaboration | Connecting ideas with examples, defining terms, causes, or consequences, listing advantages or disadvantages, using analogies to explore ideas, making connections, comparing and contrasting. | “This argument directly relates to what we talk about in class- what is the purpose of schooling? Whether to transfer knowledge or learn social skills […].” |
| Interpretation | Inferences, conclusions, summaries, generalizations, problem solution suggestions, and hypotheses. | “If I understood correctly, there is a paradox here - on the one hand, television allows everyone to freely express […]. On the other hand, there are those who control the content and dictate the narrative.” |
| Question | Question seeking to find additional information pertaining to the discussion; prompt further discussion about the current topic; a question that reflects upon the current discussion. | “I can relate and agree with this claim. But the question is- is there a better alternative?” |
| Support | Empathizing; statements of acknowledgment; providing direct feedback. | “I completely agree!” |

## 3 Findings and Discussion

Analyzing social annotations helped us understand and differentiate between several kinds of participation, trying to identify the important roles that students take.

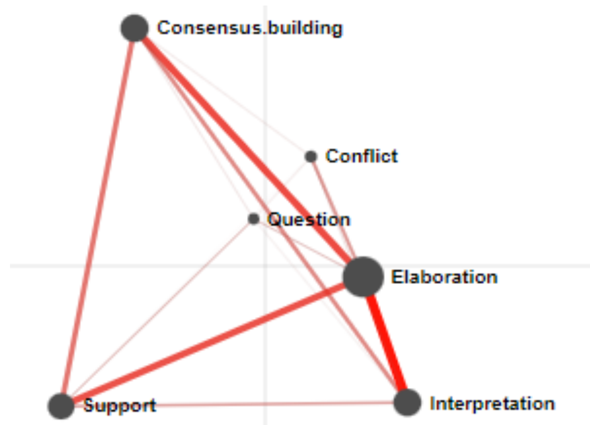


**Fig. 1.** Overall student knowledge construction network.

As seen in Figure 1, the most common knowledge construction activity was *elaboration,* which was connected to *interpretation, support,* and *consensus building*. While this pattern is in line with current work [7-8], we suggest it is vital to go beyond a broad picture and examine the various connections students make between these activities.

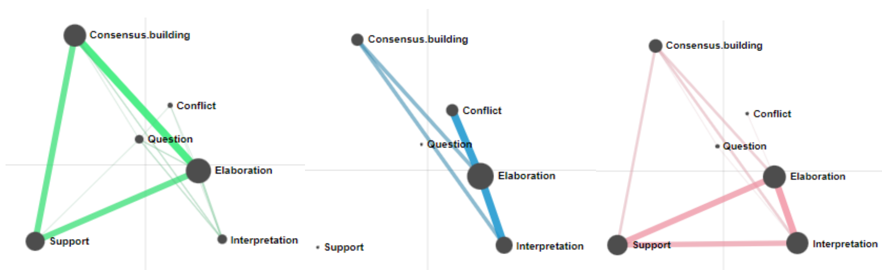


**Fig. 2.** Nina's network (left), Sharon's network (center), and Alison's network (right).

For example, Nina used annotations coded as *support* with *consensus building,* while Alison used *support* along with asking interpreting or elaborating, and in Sharon's network, *support* was not connected with other activities (see Fig. 2). This finding can help us explain the contradicting results found in previous studies. While Pena-Shaff and Nicholls [9] claim that *support* reinforces the direction of a discussion, making it a knowledge construction activity leading to further shared interpretation, Eryilmaz and colleagues [8] observed that *support* usually ended the investigated discussions rather than advancing them. Our ENA analyses reveal that while overall support did lead to *elaboration* and *consensus building* (see Fig. 1), it played very different roles in the case of individual students. Thus, we suggest that there is a need to go beyond the group level and examine the more fine-grained role different knowledge activities play for different students.

For instance, in our data we find two main prototypes with respect to *elaboration* activities: "elaborating supporter" (see Fig. 2, right) where *elaboration* and *interpretation* were related to *support*, compared with “elaborating conflictor" (see Fig. 2, center) in which conflictual comments led to *elaboration*. While these analyses are preliminary, we suggest that they illustrate the potential use of social annotation to share both agreements and disagreements. Moreover, we can see how ENA allows us to paint a more complex picture of participation, identifying typologies of participation in social annotations.

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# A Less Overconservative Method for Reliability Estimation for Cohen's Kappa

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**Abstract.** Cohen's Kappa has been used in interrater reliability calculation for decades, often for small samples. Recently, QE researchers have argued that Kappa cannot validly be used without much larger samples based on very conservative assumptions: treating all degrees of error as equally problematic and conducting an analysis analogous to statistical power analysis using a statistical significance criterion. We present a Monte Carlo analysis assessing inter rater reliability based on distance between the population Kappa and threshold Kappa (i.e., the degree of error), for a range of population Kappa values, threshold Kappa values, and sample sizes. Our findings indicate that Kappa can reasonably be used at the sample sizes often used in practice, either by raising threshold Kappa or by adopting the same stringency as statistical power analysis.

**Keywords:** Cohen's Kappa, Sample Size Calculation, Monte Carlo Analysis.

## 1 Introduction

Much quantitative ethnography research relies upon human-coded data, validated by human coders separately coding the same set of examples and checking agreement. The most frequent validation metric is Cohen's Kappa [1], which compares the actual degree of agreement to a base rate that could be expected by chance. However, there is no agreed way to compute standard error [2], making sample size calculation difficult.

Recent work in the quantitative ethnography community argues that Kappa should not be used except with very large sample sizes [3-4]. In this paper, we offer a critique of these recommendations, comparing that approach's stringency and assumptions to power analysis. We propose an alternative analysis, aligning more closely to the assumptions and degree of conservatism of statistical power analysis. We use this analysis to suggest a way for selecting appropriate sample sizes for the use of Kappa.

### 1.1 An Examination of the Methods in Eagan and Colleagues

Eagan and colleagues [3-4] presented Monte Carlo analyses testing whether a sample's Kappa is higher than the full population's Kappa. They simulated large sets of codes and repeatedly sampled from that data set. In each simulation, they specified a simulated coder base rate, and a sample size. True Kappa values (for the full population) varied 0.3-1.0 [3]. A target threshold Kappa was then selected -- 0.65 in [4] and 0.7 in [3]. Among each set of iterations, Eagan and colleagues counted the proportion of cases where population Kappa was below threshold, and sample Kappa was above threshold. They then argued that a sample size must have an error rate under 0.05 for valid use. Within this method, there are thus two steps in evaluating performance across a set of simulations: first, determining how often population Kappa is below threshold and sample Kappa is above threshold. Second, determining if this proportion is above 5%.

Note that in the first step, a coding scheme is treated as invalid if population Kappa is barely above threshold (0.69) and sample Kappa is barely above threshold (.71), treating this case the same as if population Kappa is 0.30 and sample Kappa is 0.71, while treating large differences in Kappa as acceptable if both are below threshold.

We can compare each step to statistical power analysis. For step 1, the statistical test most analogous to the case evaluation procedure in [3-4] is the Wilcoxon rank-sum test. A statistically significant value can be obtained for Wilcoxon without requiring that fewer than 5% of comparisons be in favor of the lower-valued sample; as such, this first element of [3-4] is much more stringent than statistical significance testing. For step 2, statistical power analysis typically looks for whether a significant result is seen at least 80% of the time (i.e., a failure mode occurs < 20% of the time). By contrast, Eagan et al. [3-4] look for whether a failure mode occurs < 5% of the time. As such, the second step of Eagan et al.'s procedure is four times as stringent as power analysis.

Eagan and colleagues argue that Kappa produces erroneous results more than 5% of the time for sample sizes under 400 [4] or 2000 [3], depending on base rate. They therefore argue that the common practice of testing inter-rater reliability using Kappa on samples typically much smaller than these values is flawed and should be abandoned.

In the following sections, we propose a method that more explicitly considers the degree of difference between population Kappa and sample Kappa. We also consider the implications of using a second-step stringency criterion in line with statistical power analysis rather than statistical significance testing.

## 2 This Paper's Methods

Within this paper, we analyze the risks of sample Kappa value over threshold when true population Kappa is under threshold, attempting to achieve a level of conservatism closer to statistical power analysis. Our overall process is similar in structure to [3-4]. First, we create a simulated population of 1M codes; then we sample from that data set; finally, we test whether that simulated data set represents a false positive.

Each simulation run uses three parameters: a sample size, a threshold Kappa (false positives have Kappa over threshold), and population Kappa, selected in relation to the threshold Kappa. For example, we might select threshold Kappa of 0.65 (as in [4]) and population Kappa 0.2 less than the threshold, making the population Kappa 0.45.

We then repeatedly (100K iterations) sample random data points from the population for the preselected sample size. In each iteration, we test whether the sample Kappa is above or below the threshold Kappa. Choosing both the population Kappa and threshold Kappa (in relation to each other) enables us to avoid treating small levels of variation as a false positive. We then calculate the proportion of time we have a sample Kappa above threshold, despite having population Kappa substantially below threshold.

Several sets of simulations were run. For threshold we used parameters of 0.6, 0.65, 0.7, 0.75, and 0.8; for population Kappa we used threshold (T)-0.05, T-0.1, T-0.2, and T-0.3; for sample size, we used 20, 40, 60, 80, 100, 200, 400, 500, 800, 1000, and 2000.

See [bit.ly/3wRhrt4] for software used in these simulations.

## 3 Findings

Having created these simulations, we can now check for the proportion of time a specific test produces a Kappa above threshold, despite having a lower population Kappa.

We consider first a sample size of 60 (see Table 1) – a small dataset, but of a size seen in QE inter-rater reliability checks. Table 1 reports the proportion of samples with a Kappa value above threshold, when the true value (population Kappa) is some amount (or more) less. We note that for this sample size, across all thresholds, there is a high probability (~30%) that sample Kappa was more than .05 larger than population Kappa. Therefore, for this sample size, there is high risk that a sample Kappa value barely over threshold may represent a population Kappa value barely below threshold, regardless of what that threshold is. As we increase the distance between threshold Kappa and the population Kappa (from .1 to .3), the number of samples that meet the threshold drops, with less than 1% of samples achieving threshold Kappa .3 or more above population Kappa value. These results are fairly consistent between thresholds of .6 and .75 but there is lower error for a .8 threshold. Overall, if a researcher selects a level of conservatism comparable to power analysis (under 20% error), even a small sample of 60 data points is sufficient to be confident that a threshold is unlikely to represent population Kappa over 0.1 below threshold. If a researcher chooses conservatism comparable to statistical significance testing (5%), 60 data points is still sufficient to be confident that a threshold is unlikely to represent a population Kappa more than 0.2 below threshold.

**Table 4.** The proportion of cases where Population Kappa was more than specific distances (rows) below Threshold Kappa (th) (columns), for a sample size of 60.

| | | Threshold Kappa (th) | | | | |
|---|---|---|---|---|---|---|
| | | 0.6 | 0.65 | 0.7 | 0.75 | 0.8 |
| | th - 0.05 | 0.316 | 0.316 | 0.274 | 0.300 | 0.242 |
| Population | th - 0.1 | 0.175 | 0.175 | 0.139 | 0.151 | 0.107 |
| Kappa | th - 0.2 | 0.035 | 0.035 | 0.024 | 0.025 | 0.014 |
| | th - 0.3 | 0.005 | 0.035 | 0.003 | 0.002 | 0.001 |

We further investigate the impact of different sample sizes in Table 2, considering sample sizes ranging from 20 to 800. We note that very small differences between threshold Kappa and population Kappa can be achieved for large samples.

**Table 5.** The proportion of cases where Population Kappa was more than a certain distance (columns) below Threshold Kappa, for varying sample sizes (rows).

| Sample Size | Population Kappa (Threshold Kappa) | | | | |
|---|---|---|---|---|---|
| | 0.55 (0.6) | 0.5 (0.6) | 0.75 (0.8) | 0.7 (0.8) | 0.6 (0.8) |
| 20 | 0.399 | 0.307 | 0.292 | 0.196 | 0.081 |
| 40 | 0.350 | 0.231 | 0.265 | 0.144 | 0.035 |
| 60 | 0.317 | 0.175 | 0.243 | 0.108 | 0.015 |
| 80 | 0.292 | 0.145 | 0.218 | 0.082 | 0.007 |
| 100 | 0.269 | 0.117 | 0.197 | 0.061 | 0.003 |
| 200 | 0.193 | 0.047 | 0.126 | 0.016 | <0.001 |
| 400 | 0.112 | 0.009 | 0.054 | 0.001 | <0.001 |
| 800 | 0.042 | <0.001 | 0.014 | <0.001 | <0.001 |

# 4 Conclusions

Overall, our Monte Carlo analyses show that the situation for Kappa is not quite so grim as Eagan et al. [3-4] argue. Whereas they argued that Kappa could only be confidently used for samples of 400 [4] or 2000 [3] data points or higher, we find that only small differences are seen for much smaller samples. Our results indicate is that if we are willing to accept that a sample Kappa may be slightly higher than a population Kappa, fairly small sample sizes are needed to use Kappa with confidence. If we are willing for a threshold Kappa of 0.6 to actually represent a population Kappa of 0.501 5% of the time, then a sample of 200 is sufficient. If we are willing for a threshold Kappa of 0.8 to actually represent a population Kappa of 0.751 20% of the time, or for a threshold Kappa of 0.7 to actually represent a population Kappa of .601 10% of the time, then a sample of 100 is sufficient. Even a very small sample of 40 can be acceptable in some cases -- for instance, if we are willing for a threshold Kappa of 0.8 to actually represent a population Kappa of .701 20% of the time. In other words, our findings provide evidence that Kappa can be acceptable for many uses and assumptions, even with smaller sample sizes than our community typically uses. With a larger sample, our estimate of Kappa can be more precise. But the cost of this is more time spent in coding data for inter-rater checking. [3] argues that so much data must be coded to use Kappa that Kappa is essentially infeasible - our findings suggest otherwise.

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# Researching Relational Agency and Inclusive Learning Communities through a Virtual Internship

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**Abstract.** This paper outlines a virtual internship designed to provide trainee teachers with opportunities for experiential learning by engaging them in authentic school situations. Using epistemic network analysis, data collected from the virtual internship will help us understand the development of relational agency among teachers and characteristics of an inclusive learning community.

**Keywords:** Agency, Virtual Internship, Epistemic Network Analysis.

## 1 Introduction

The COVID-19 pandemic forced educators around the world to reflect on their educational priorities. School closures during lockdowns that were instituted as a response to the pandemic had negative effects on learners at all levels, especially those at risk of exclusion. The pandemic also highlighted the importance of collaboration within professional learning communities to help teachers navigate the crisis and respond to challenges presented by the disruption to normal teaching practices [1].

The involvement of teachers in professional learning communities can have a transformative impact on changes to teaching practices [2]. These can be defined as groups of people that share ”teaching practices and collaborative inquiry processes in which analyzing, reflecting on, and improving teaching practices is key” [3, p. 11]. These communities go beyond being a group of individuals that happen to work together, as they are characterized by having shared values and acting together to achieve shared purposes. This sharing of resources and collaborative work toward a specific goal was key in teachers' responses to the COVID-19 lockdowns, as it allowed them to work with each other to quickly adapt their practices to the new realities of online teaching by allowing more technologically experienced teachers to support less technologically experienced ones and the sharing of best practices among teacher networks [1].

Given the importance of these professional learning communities in teachers' responses to the COVID-19 pandemic, there is an urgent need to understand how people build and sustain them - i.e., to understand authentic reasons why people reach out to others for support as they seek to solve problems. Previous research has shown that teachers tend to engage in these kinds of collaborative interactions in situations when they display relational agency, that is, when they engage in pro-active solution seeking rather than simply implementing their roles [4]. Therefore, relational agency is a useful framework to understand how teachers work flexibly and purposefully with other actors to remove barriers and promote all students' learning [5, p. 234].

Our study seeks to address this need by studying how teachers interact with each other in collaborative activities and how their agency develops with the use of Epistemic Network Analysis (ENA), which is an analytic method that can help understand the structure of connections and the strength of association between elements in a network [6]. In the context of this study, it can be used to understand how important aspects of relational agency such as purpose, interactions and context are present in the ways in which student teachers collaborate to solve problems. Accordingly, our research will be guided by the following questions:

1. How can a virtual internship for teachers facilitate the development of relational agency?
   (a) What does relational agency look like in a virtual environment through interactions with actors within a network?
   (b) How do these interactions change over time?

## 2 Methodology

### 2.1 Data Collection

Data for this project will be collected through the development of a virtual internship. Virtual internships are computer-based professional practicum simulations where participants assume the role of a professional, working collaboratively on authentic tasks and engaging in complex professional thinking. These simulations employ authentic professional training practices that integrate action and reflection to develop expert-like thinking skills [7].

The virtual internship therefore aims to provide pre-service teachers with opportunities for experiential learning by engaging them in authentic school situations which require them to collaborate to address challenges related to online education.

**Design of the Virtual Internship.** The virtual internship was based on scenarios obtained from a previous research project which examined the experiences of pre-service and in-service teachers in Scotland and Australia during the COVID19 pandemic[1]. One of these scenarios, for example, addresses the struggle many teachers experienced during the COVID-19 lockdowns in engaging students with online classes and ensuring that they participated in both the synchronous and asynchronous learning activities. Interns are given an explanation about the 'issue' that is being faced by the

[1] https://sites.google.com/view/bacovid/

school where they are ”placed” and background on the school itself. They will then spend the next five weeks collaborating with their mentors and the other interns to create a solution that will help improve student engagement in their ”placement” school.

The virtual internship will consist of 5 weeks during which participants will be scaffolded in the development of their agency with a series of questions based on the Agents of Change Toolkit [8]. This toolkit models agency around five steps: checking the purpose, agreeing on outcomes, negotiating a plan, enacting it, and evaluating and reflecting on it. The virtual internship will emphasize making the interns think on how they can harness networks to face the challenges that are presented to them. For example, in the third week of the virtual internship, interns will create an action plan by discussing how they can tap into their networks to solve the challenge and answering the week’s guiding question: ’who can do what, when and how?’.

Data on how students engage with their professional networks and proactively work toward exercising their agency in the proposed scenarios will be collected through live chats in which small groups of students will collaborate and find joint solutions, and forums used for different groups to give each other feedback on the solutions at key points in the internship.

### 2.2 Data Analysis

Given that relational agency is all about interactions and how teachers use their networks purposefully to solve problems or bring about change, ENA can be used to map the elements that make up relational agency within their networks and help us understand what relational agency looks like in the context of our virtual internship, from the point of view of the purpose of those interactions and the interactions themselves.

As mentioned previously, this study is part of a broader research project that focused on how teachers exercised their agency to respond to the challenges posed by the COVID-19 lockdowns. One of the main findings of that project was on the purpose of interactions within professional learning communities: teachers turned to their networks to share resources and best practices, to collaborate with each other in the creation of materials, and to ask each other for advice for dealing with specific situations or using certain technologies.

Another important dimension to capture is the nature of those connections. The broader research project found that there were differences in the types of networks used by in-service teachers and pre-service teachers, given that the former had more established networks than the latter. Therefore, it seems relevant to capture whether these networks include other teachers, specialists, leaders, mentors or broader social media.

Finally, we are interested in studying how these connections change and develop over time. ENA allows us to compare the epistemic networks created around relational agency at the beginning and at the end of the virtual intern ship, as well as the strength of the connections made by participants regarding the purpose and type of interactions they experienced.

## 3 Conclusion

COVID-19 pandemic forced teachers to quickly adapt to the new realities of lockdowns and online learning. There is evidence that the use of networks and professional learning communities were essential in helping them make this transition [1]. It is therefore important to understand how these professional learning communities are formed, and how we can help develop and nurture these interactions. This study seeks to address this need through an analysis of how relational agency looks like and develops for student teachers during a virtual internship to better understand how they develop and how they can be facilitated in future iterations of the internship.

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# Expanding Fairness in Game-Based Assessment with Quantitative Ethnography

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**Abstract.** Game-based assessment (GBA) leverages the dynamic, authentic nature of games and numerous data generated from gameplay to make inferences about learners: what they know and can do. So far, standard data science and psychometric practices have dominated the field regarding how to make sense with game telemetry data using computational methods. However, GBA are vulnerable to myriad threats violating validity that can lead to unfair inferences as well as treatment of different subgroups. In this poster, we discuss how Quantitative Ethnography (QE) can help the field expand the notion of fairness in GBA.

**Keywords:** Game-Based Assessment, Fairness, Quantitative Ethnography.

## 1 Introduction

Game-based assessment (GBA) is a specific use of educational games that employs game activities to elicit evidence for educationally valuable skills and knowledge [1]. GBA offers three unique affordances: (1) Because students associate games as a leisure activity for fun, they might feel less stressed compared to traditional assessment [2]; (2) The assessment can be unobtrusive without interrupting the flow of the game by using in-game measures as evidence that can be fed into assessment models [3]; and (3) Because games allow eliciting rich data about different processes and strategies for problem-solving, students can receive personalized and tailored feedback specifically targeting challenges that student is facing [4].

The core element of GBA is making claims about what students know and can do based on the evidence that can be observed from their gameplay. Different methods from psychometrics to data science and learning analytics have been applied, including rule models [5], performance indicators [6], and knowledge inference algorithms [7].

However, one question that has yet to be foregrounded is: In terms of qualities integral to assessment, such as validity and fairness, how does GBA fare? Moreover, GBA requires new ways of examining these qualities [7] because gameplay data can easily violate assumptions required for traditional statistical analysis (e.g., an underlying latent variable stays static and has a normal distribution). While state-of-the-art analytical techniques can be helpful in examining these qualities, they are not free from ethical concerns related to algorithmic biases as [8] pointed out.

In this poster, we specifically focus on the issue of *fairness* in GBA—we seek to expand the idea of fairness in GBA by leveraging QE perspectives. Some of the questions that guide this exploration include: *How do we know if the GBA is fair? Can applications of QE provide more nuanced insights about fairness in GBA? If so, what are the affordances of QE as a framework to expand fairness in GBA and beyond?*

In the following sections, we briefly discuss the notions of fairness in GBA and QE and propose two areas of GBA in which QE practices can expand fairness. Lastly, we present a sample analysis as a proof of concept, using data from a computer-based puzzle game called Shadowspect.

## 2 How QE can expand fairness in game-based assessment

The term *fairness* has been defined in a wide variety of ways in different fields. According to Mislevy, fairness in educational assessment is framed as either (a) *marginal* fairness or (b) *conditional* fairness [9]. Marginal fairness refers to what extent assessment could be designed and administered in a way that all examinees would respond in the same form, and to what extent their performance would be evaluated with the same procedures. Often associated with comparative validity ("a fair test is one that yields comparably valid inferences from person to person to group to group, p. 214) [10], this sense of fairness requires the construct-irrelevant features to be minimized. Over the years, a substantial body of work has examined and applied the concept of marginal fairness in their assessment design and research.

Recently, however, it has been suggested that fairness in assessment should be understood *conditionally* using conditional inferences – that is, instead of treating context-related factors that influence inferences as a noise, we can take them into account when making inferences about one's performance on assessment tasks. With the conditional sense of fairness, one is no longer limited to the idea that all students need to provide the same behavioral evidence in relation to latent constructs as long as the resulting evidence is comparable.

While limited, there are a few studies that investigated the issue of fairness in the GBA contexts. For example, Kim and Shute [11] compared male vs. female and gamer vs. non-gamer students' performance with two versions of Physics Playground (i.e., linear vs. non-linear progression). This study concluded that the game has an unfair advantage for male gamers compared to the other groups, using the two-way ANOVA model. However, these standard analytical methods to examine fairness in assessment remain at the marginal fairness level and fall short of identifying various sources of biases and can't pinpoint how they interact with the dynamic nature of how people demonstrate various skills in games. In addition, as Halverson and Owen [1] pointed out in their assessment data aggregator for game environments (ADAGE) framework, that the inference made using data in GBA often ignores the larger social context of the games. This implies that we must broaden the way we address fairness in the design and development of GBA as well as situate the assessment in a broader sociocultural frame to better assessment models. Extending game plays well beyond the game itself and contextualizing what the game plays mean in a wider sociocultural lens can shed light on the context of a certain subgroup or individual that may have led to the assessment results.

In this poster, we suggest two ways that QE practices can attend to those needs that can increase fairness in GBA (See Fig.1).

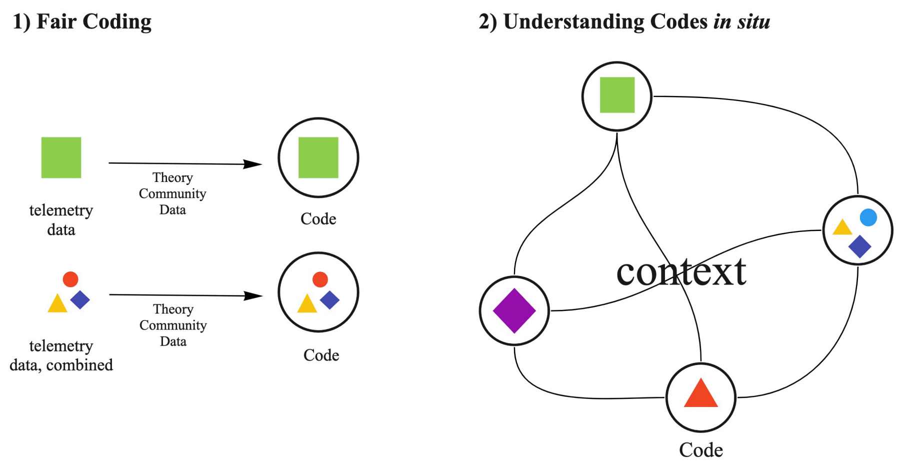


**Fig 1**. An illustration of two-levels of GBA that can intersect with QE.

1) Fair coding: According to Shaffer and Ruis, a [C]ode refers to a meaningful concept or construct that constitutes a Discourse, and a [c]ode is a collection of features in the data that we use to claim that the [C]ode is present [12]. In GBA, coding is related to building computational models of gameplay data, particularly to the process of building knowledge engineered or machine-learned (mainly supervised) assessment models using distilled features from the telemetry data. In other words, a feature or the combination of the features from raw telemetry data becomes a systematic construct in assessment through the process of coding. It is important that coding is fairly done because these [C]odes are used to build one's assessment model. In order to establish fair coding, a [C]ode should be a fair representation or interpretation of the community being studied, of theory, and of the data itself. Specifically, the practice of closing the interpretive loop in [C]oding allows to examine whether [C]odes are fair to the data by examining how certain features are coded for those [C]odes. While principled approach to assessment design such as Evidence-Centered Design [13] intends to increase fairness to theory in a similar way, it does not support rapid iterations of the model based on qualitative examination of the data.

2) Understanding Codes *in situ*: Examining how those [C]odes are used and interconnected among themselves *in situ* can provide a more nuanced understanding of the skill estimations in actual contexts, particularly by accounting for existing

individual and group differences in the usage or connection of the [C]odes. For example, Epistemic Network Analysis (ENA), developed by Shaffer and colleagues [14], creates a representation of an individual's or group's ways of thinking, acting, and being in the world of Community of Practice [15, 16]. Furthermore, Hierarchical Epistemic Network Analysis (hENA) enables comparison of two ENA networks while controlling for certain factors [17]. In ENA, contextual factors are no longer treated as a noise, but as an important clue in making inferences of one's performance.

## 3 Working Example

We propose to apply forementioned QE practices to data sourced from Shadowspect to explore how QE as a methodology can expand the concept of fairness in GBA. Shadowspect is a 3D puzzle game that aims to explicitly measure common core geometry standards (e.g., visualize relationships between 2D and 3D objects), spatial reasoning skills, and persistence. First, we will apply the practice of fair coding—that is, mapping the log data into meaningful constructs in assessment—by using relevant theories and discussing them with the teachers who implemented the game in their classrooms. For example, a code or a feature that measures how long a user spent for incomplete puzzles can be mapped to a [C]ode of persistence based on existing theories. Also, the coding scheme created from this practice can be compared to the estimations provided by the machine learning practices. Furthermore, based on these Codes, we will then build ENA models that show subgroups of interest using meta data of each player. Some of the grouping variables that we will use are: gender, math self-efficacy and anxiety, math grade, enjoyment with the game, and gaming experience.

Figure 2 demonstrates how ENA could be used to expand fairness discussion in GBA. In our previous work , for example, a Random Forest model was used to provide evidence that neither group is unfairly advantaged (Kim et al., under review), however, when we plotted the aggregate features—those known to contribute to estimating one's spatial reasoning—using ENA, it allowed us to investigate how these features might have a different "weight of evidence" [7] per subgroup (See Fig. 2).

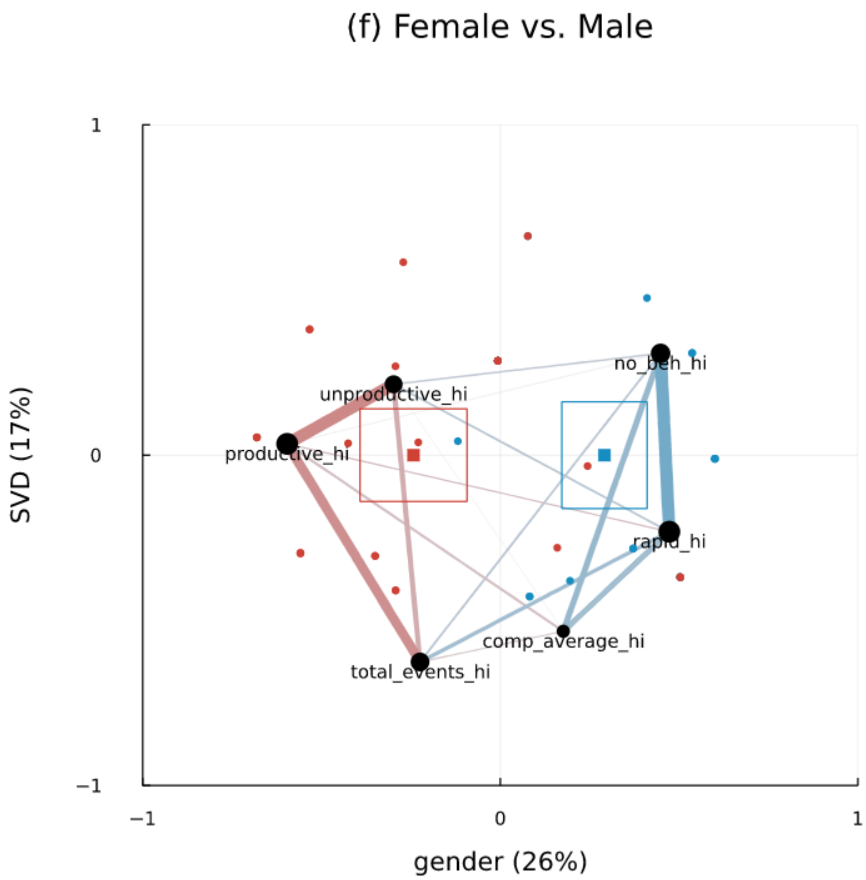


**Fig 2**. An ENA model that compares the pattern of spatial reasoning for girl group and boy group.

## 4 Conclusion

In this poster, we argue that applying QE practices in GBA could expand how we examine fairness in GBA by helping the "coding" process of in-game features fair to data, theory, and community. In addition, QE methods could illuminate subgroup differences considering the context beyond simply comparing model accuracy at the aggregate level. In future work, we will develop Shadowspect assessment models using QE methods and investigate how QE-informed models differ from the standard data science models in terms of fairness.

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# Code-wise ENA: A Sequential Representation of Discourse

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**Abstract.** A variety of research contexts involve the tracing of ideas over time. That is, the unit of analysis just is a shift from speakers to codes themselves. We present a method for shifting these units in Epistemic Network Analysis.

**Keywords:** Epistemic Network Analysis, Trajectories, Units of Analysis, Collective Storytelling, Emancipatory QE.

## 1 Introduction

In collective storytelling, ideas are repeated or reverberated across a group [1]. In participatory emancipatory research, researchers trace how such ideas circulate among members of groups under study, elucidate how they build on each other and collectivize the work of such groups, and attentively present the values, tensions, and resistances of such collective action [2].

Code-wise Epistemic Network Analysis (ENA), the method we present, emerged from a cross-disciplinary collaboration. From nursing education technology [3-4] to early childhood development [5-6] to collective storytelling [1-2, 7], there is common interest in tracing a set of ideas, over time, and in relation to one another. Put another way, this focus *just is* a shift in unit of analysis, from speaker to code. This is one of the affordances Quantitative Ethnography provides: a way to model and understand how each of one's codes is deeply dependent on its connections to other ideas [8]. But existing ENA trajectory methods only model aggregate ideas of an individual or group rather than a particular idea itself, or they require *a priori* a way to split temporal data into smaller time periods [9-10]. Therefore, in this poster we build on these developments, shift units of analysis, and model and visualize the changes of particular codes over time.

## 2 Proposed Method: Code-wise ENA

Our use of ENA trajectories differs from others only in how we define our units: We define units to be each "chorus" of each code. That is, each code appears multiple times throughout the conversation, resulting in multiple segments of the conversation during which the code will always be in context or "in window" during ENA accumulation (See Fig. 1). Imagine some songs, where a chorus reappears without changing meaning: the code's qualitative concept repeats but holds steady connections. Or other songs, where a later chorus has a different meaning than an earlier one: the context changes, the meaning takes on new light, and the connections of the code shifts in response. By defining our units as these choruses, we are able to (i) model how the contexts of codes (overlapping and shared among other codes) shift throughout time; (ii) shift focus from speakers to the mixing and reverberations of their ideas instead; and (iii) do so without arbitrarily splitting the conversation into time segments.

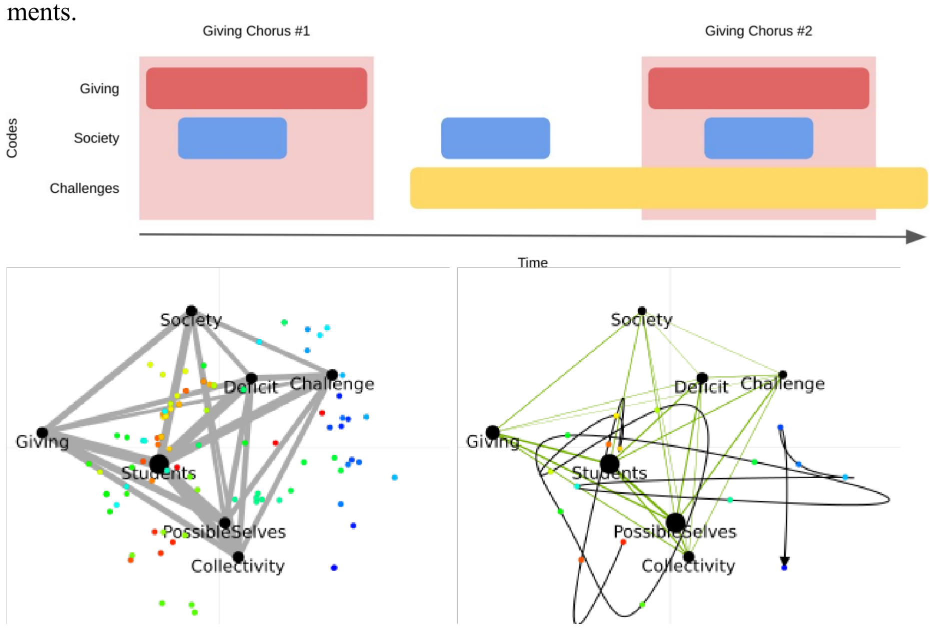


**Fig. 6.** A hypothetical illustration (top), overall model (left), and model of possible selves (right) using code-wise ENA.

## 3 Example: Collective Storytelling

Our example is a part of a larger study of twenty participants, teachers from an urban indigenous school in Thailand, from five different ethnicities/tribes in Thailand (Karen, Lanna Thai, Lahu, Akha, Isarn Thai), and with teaching experience ranging from five to over twenty years. Their subject areas included English, Thai, Mathematics, Social Studies, Mathematics, Chemistry, and Special Education. The study involved a two-day camp in 2015 where participants came together during a session named "the web of passion." Seven of the participants were former students of the school where the camp was held. The focus of this session was for participants to share stories of how and why they came to be educators and in what ways a new practice (Tutor´ıa) fit into their visions of educational and social change. This session depicted connections between stories with a ball of string: The ball starts from a point and goes around the room as each participant shares their stories, holds onto part of the string, and passes the ball along. These stories were recorded, transcribed, and coded iteratively using social moderation, member checking, and participatory analysis [7]. For this poster, we explore how, through sharing their experiences, these teachers connect past, future, the broader teaching community, and their immediate community.

Our model (See Fig. 1) explained 44% of overall variance ($R_x^2 = .25$, $R_y^2 = \cdot$ 19), and there was a high goodness of fit between model and graphical representation (co-registration Pearson $r > .99$ along both axes). The x-axis appears to capture a Motivation dimension, from motivations around *Giving* on the left to motivations around *Challenges* on the right. And the y-axis appears to capture a SocialSphere dimension, from *Society* writ-large on top to a shared sense of *Collectivity* with others in the room on the bottom.

Overall, at the beginning of the storywork event, some teachers mentioned giving or being givers as part of their purpose of becoming teachers. One talked about being "the givers who want to see others move forward so that they can get many other things." As the stories continued, teachers envisioned children also being givers or contributors to learning. Then, across their stories, the collective sentiment of purpose shifted (x-axis) from giving to challenges. While teachers are often giving of themselves all the time, the challenges that the school and Indigenous children face continue to act upon their everyday lives. Although counter-intuitive, reminders of the historical, institutional, and everyday challenges the team were facing together became a lever of renewed purpose and motivation. Moreover, these challenges came up alongside visions of possible collective selves (y-axis). For example, "I want to try, but this attempt doesn't depend upon myself." This shared vision of possible collective selves included both (i) felt stories around pain, frustration, and anger at the ongoing dehumanization and deficit-orientations to Indigenous teachers and children [11]; and (ii) the felt possibilities to "decide to be in the same boat," to imagine an otherwise world collectively. This talk around possible selves alternated between thinking like a collective and the collective's roles/impacts in society beyond the confines of school (See Table 1).

**Table 6.** Codebook

| Code | Definition | Example |
|---|---|---|
| Challenges | Felt tensions encountered within the team, in relation to school curriculum or goals, or in relation to future goals and past/present/future realities | "I was not sure if all of the teachers would accept and get the thread to join in" |
| Collectivity | Conviviality, social dreaming, becoming a "we" | "Many people talked to one another and we were in friendly atmosphere during tutoring" |
| Deficit | Inability to do something or to not do it well | "They don't...it seems like they do not have confidence in themselves" |
| Giving | A sense of giving, offering of knowledges, or skills | "I want to give knowledge to them" |
| Possible Selves | Potential for change and different possible futures, imagination | "This reveals... potentials of their students and leads to more acceptance" |
| Society | Teachers' narration of societal realities and challenges | "There are many dangers such as the different kinds of crimes, robbery... that surround us" |
| Students | Students' knowledges, practices, and abilities | "They also will not dare to speak even though they had got held or caught" |

## 4 Discussion

Code-wise ENA emerged from collaboration with colleagues facing a similar structural challenge in a number of contexts. In research on collective storytelling, nursing education, and interest development, there is a common need for modeling and tracing ideas over time, not (just) a trace of the trajectories of individual speakers or groups. Shifting one's unit of analysis to codes themselves allows one to zoom in on the sequence of events participants follow, skip, or return to repeatedly as they master skills, develop ideas, and build on one another. And a representation of such a shift of unit could provide a new way to make sense of constructs and reflect on the design of interventions with a variety of stakeholders.

However, code-wise ENA currently faces two challenges. One, as with existing trajectory methods, splines are used to aid in the interpretation of meaningful trajectories through one's data. However, splines can suggest patterns that are absurd. And two, given a large number of codes, it is not clear to us yet how one should best select which have similar enough trajectories to discuss in tandem and which stand out.

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# To Affinity and Beyond: Tensions to Tackle to Legitimize Participation by Aspiring Programmers

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**Abstract.** This study aims to examines how aspiring programmers describe their experiences of either seeking or offering help on online discussion forums. Epistemic network analysis (ENA) was used to identify the underlying structures and patterns of connections in the discussion of programming communities in Reddit. Models showed that discussion in subreddit named r/Askprogramming was more focused on how help-seekers can better legitimize their participation by following the community norms. In comparison, more diverse aspects of help-seeking processes were addressed in r/learnprogramming. This study offers insights into the patterns of associations in Reddit posts through the lens of those who are relatively new to the community as they endeavor to gain legitimacy. Also, it expands previous discussion on the affordance of ENA to not only communicate but also involve participation from a broader audience, in this case learners in discussion forums for whom quantitative ethnography may be used to inform the design of a safe space for brokering opportunities beyond an affinity.

**Keywords:** Affinity Spaces, Discussion Forums, Programming, Stack Overflow.

## 1 Introduction

To learn is to engage in a discourse with those with shared interests, experiences, and pursuits, or an affinity [1]. Particularly, programming as a field has been recognized for its community-driven endeavor cutting across a wide array of online communities such as Stack Overflow, Github, Discord, and Reddit. However, the process of enculturation through peripheral participation in these distributed venues of informal learning is often challenging for newcomers who have not been formally introduced to the set of beliefs, values and norms that govern the discourse of the community [2]. In fact, research has found that newcomers often face barriers when they seek support for their challenges and subsequently their limited participation strain the virtuous cycle of community through which a new generation of developers should be nurtured [3]. Most studies have focused on how novices could fall short of the experts' language and behaviors when looking for help on specific platforms [4], or how technology could be leveraged for improved usability [5]. Few studies have explored the tensions arising from varying scope of exposure to programming, expectations, and experiences specifically through the lens of novices as they seek learning opportunities in online communities. This work explores how aspiring programmers describe and discuss their experiences of seeking or offering help online across three programming-related sub-communities in Reddit.

## 2 Methods

Threaded discourse data (18 threads, 2771 comments) was selected across three programming communities in Reddit (r/learnprogramming, r/AskProgramming, r/ProgrammerHumor) on the basis of being as recent as published within three years, moderately robust with at least 30 comments, and relevant by using search terms such as "asking for help" and "communities" to find discussions focused on help-seeking in online venues like Stack Overflow. All comments were collected with the exclusion of those either deleted by the user or posted by a deleted user. For this poster, the 6 most popular threads have been used for creating the epistemic networks.

Six codes were developed based on an inductive examination of the data that was grounded in the context: Help-seeker Behavior, Helper Behavior, Question Quality, Help Quality, Community Norms, Help Self. Once codes were identified, three rounds of deductive coding were conducted between two researchers until strong levels of interrater agreement were reached. For analysis, the preliminary model was generated using the ENA Web Tool with individual posts as line of data and a thread as unit variable. An infinite stanza window was chosen to account for the way discourse was structured and driven in Reddit. Atypical of most natural discourse, posts are automatically listed for users in the order of best comments, based on proportion of upvotes to downvotes, rather than chronologically. It was also expected that the posters engage in the discussion according to this ordering, as evidenced in a poster's referencing back to earlier or more well-received post (e.g., "If you read my post you would know that the issue I had was that I couldn't find the answers to my questions.").

**Table 1.** Codebook and Code Validation

| Code | Definitions and examples | rho | kappa |
|---|---|---|---|
| Help-seeker Behavior | Discussion of what programmers with little experience, should or should not do when asking for help<br><br>e.g., "you should definitely be able to find the resources you need, like basic tutorials… through google." | 0.00 | 0.86 |
| Helper Behavior | Discussion of what programmers with relatively more experience should or should not do when offering help<br><br>e.g., "Half the time people … unnecessarily downvote it. Waste time asking why I'm asking a certain question" | 0.00 | 0.92 |

| | | | |
|---|---|---|---|
| Question Quality | Description of what makes a question good or bad, or "worthy" of posting or being addressed<br><br>e.g., "An ideal question requires no back-and-forth. A good question only requires further clarification" | 0.00 | 0.90 |
| Help Quality | Description of what makes helping good or bad, or what is "helpful" for learning<br>e.g., "I tried the solution but unfortunately it didn't work. The dude's response was something along the lines of "well it should"." | 0.00 | 0.92 |
| Community Norms | Negotiations of what the community is for<br><br>e.g., "If your question is not helpful to other people then it doesn't belong on SO." | 0.00 | 0.96 |
| Help Self | Discussion of, or an allusion to the importance of programmer making self-directed efforts in the process of finding help<br><br>e.g., "I always have found the answer to my problem or at least close enough to point me in the right direction for me to figure it out on my own." | 0.00 | 0.94 |

## 3 Preliminary Results

The models (See Fig. 1) showed both similarities and differences in how aspiring programmers described their help-seeking narratives across communities in Reddit, or subreddits. In r/AskProgramming, the connection between Help-seeker Behavior and Community Norm (0.37) was the strongest. Dedicated to addressing programming questions like Stack Overflow, the members of subreddit r/AskProgramming tended to focus on the help-seekers' behaviors to provide justification for their perceived difficulty of finding help online. Often, their failed attempts to find the needed help or involvement with negative experiences would be attributed to the newcomer's own incapacity to follow the community norms. For example, on a thread where the author shares the beginner's frustration of getting negative responses for asking basic questions in Stack Overflow, a member explained that "It's not a platform to ask beginner questions and the people aren't there to act as your teacher. While there are some parts of the platform that could be better, it's not toxic if you don't misuse it." Likewise, another member articulated that newcomers should earn legitimacy by conforming to the rules, saying "You not taking the time to learn how the community works before trying to participate is a problem with you, not the site." Such an assumption of help-seeker accountability, unfortunately, rendered aspiring programmers to take advantage of the community but not necessarily take a part in it, as evidenced in a comment admitting "I have just realized that it is not where I belong. I belong reading SO, not contributing."

On the contrary, most of the connections between the codes were similarly strong in r/learnprogramming. In particular, Help-seeker Behavior and Help Quality being most strongly connected (0.35), suggesting that the members might explore the different aspects of help-seekers' experiences in a way that the aspiring programmer can better understand what makes it mutually productive for communication purposes as well as more conducive for the goal of learning programming. For example, a member advises the author, saying "when you have a problem try to analyze all the steps, then search for a very specific thing" In a similar vein, another member shared personal experience: "when I put a lot of effort into crafting a question, spent a day or two exploring what exactly I was unsure of, I've had amazing responses." While the connection remained strong between Help-seeker Behavior and Community Norms (0.33), it was also strong for Help-seeker Behavior and Helper Behavior, showing the members tended to show a more balanced view on the experience by recognizing how helpers may behave in a discouraging way for help-seekers. In line with this interpretation, a member lamented that, "I really do not understand downvoting without giving an explanation of why." Similarly, another member shows agreement saying "They forgot … that one that they were beginners too. … when you have a problem try to analyze all the steps, then search for a very specific thing … harder to find solutions for not specific things." In summary, aspiring programmers who are seeking help in online communities may benefit more from a holistic approach than a focus on querying as a reflection of their potential.

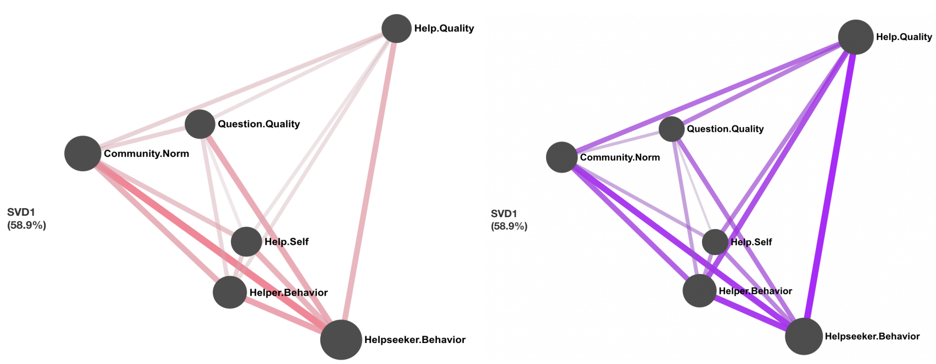


**Fig. 1.** Models from r/AskProgramming, and r/learnprogramming respectively, both of which had 1.00 goodness of fit for Pearson and Spearman.

## 4 Conclusions

This work expands upon prior research in the field of quantitative ethnography studying collaborative learning and engagement in online spaces by identifying differences in discourse across different programming communities in Reddit. The preliminary results demonstrate what is highlighted or neglected in the aspiring programmers' discourse in different spaces, which inadvertently hold novices accountable for earning legitimacy for their own learning. While both communities were designed to address questions on programming, r/AskProgramming would focus on community norms whereas various aspects of discourse were raised in r/learnprogramming in line with an emphasis on "learning" in its name. Future work will explore how the design of these affinity spaces might rebalance the tilted share of responsibility to support the growth of as well as perpetuate the legacy of programming communities.

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# Using Contextual Engineering to Inform Coastal Resilience Decisions in the Great Lakes Region

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**Abstract.** Anthropogenic activity has led to an increase in intensity and frequency of extreme climate events, including coastal flooding and erosion in the Great Lakes region. Novel and adaptive infrastructure solutions to coastal resilience are needed to address the anticipated damages to ecosystems, human quality of life, and infrastructure due to climate change. Contextual Engineering is an emerging quantitative ethnographic framework that can be used to determine the appropriateness and adoptability of infrastructure technologies. The Contextual Engineering methodology transforms observations and experiences surrounding the 5 contextual influences (cultural, educational, political, mechanical, and economic) into quantitative data to aid decision making in complex systems. This paper outlines how Contextual Engineering will be used to facilitate technical decision-making for appropriate coastal resilience techniques in three testbed communities in the Great Lakes.

**Keywords:** Contextual Engineering, Coastal Resilience, Decision-Making Tool, Decision Matrix, Quantitative Ethnography.

## 1 Introduction

The Great Lakes basin, one of the world's largest supplies of freshwater, has experienced region-wide warming over the last several decades [1]. This warming has led to an increase in both the frequency and magnitude of extreme events, producing coastal flooding and erosion, which threaten local ecosystems, human health, and property [2]. Climate change is complex, with concurrent and interacting social and climate factors that can compound damage and losses [3].

Coastal resilience is a particularly complex issue in that shoreline stabilization solutions developed by one community can have a direct impact on erosion elsewhere in the lake basin. Existing shoreline stabilization techniques range from green to gray infrastructure (Fig. 1). While gray infrastructure techniques offer engineering solutions, they often are not sustainable in a rapidly-changing environment, and they may actually cause ecological harm [4]. Furthermore, these structures are notoriously non-aesthetic. Although gray infrastructure offers predictable and quantifiable technical solutions, it is unable to adapt to rapidly changing conditions. Researchers should instead focus on developing adaptive solutions [5]. Not only are gray infrastructure techniques temporary, but they can also fragment or destroy existing habitats and alter biodiversity [4]. Furthermore, they typically have a high cost, high embodied energy, and high material use [6].

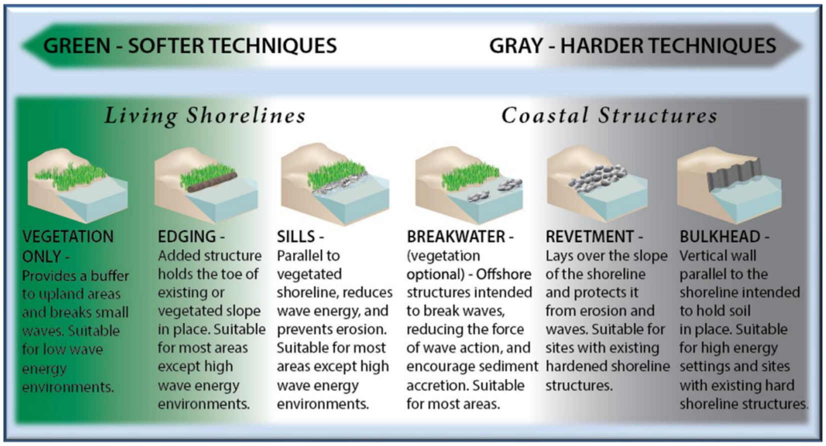


**Fig. 7.** A range of shoreline stabilization infrastructure solutions ranging from green to gray techniques presented in [7] and reprinted from [8].

Nature-based solutions include natural elements or structures that mimic natural features [6]. These approaches can adapt to climate-change induced water-level rise and extreme weather events, cost less to construct and maintain, and provide habitat for local wildlife [6]. Vegetation can also self-recover after extreme events, but the root structures can take years to establish [9]. Additionally, due to a lack of research, scientists and engineers have a limited understanding of how these structures will hold up over time, so they require substantial design, testing, and monitoring. An added challenge is that each physical and social context requires a specific solution, so design solutions are not easily scalable across a region or lake basin [4].

This study applies quantitative ethnography (QE) to complex decision making through the use of Contextual Engineering (CE). CE is a technical design process used by researchers and engineers to identify and apply scientific, mathematical, social, and place-based knowledge to address physical challenges based on a community's needs and a designer's understanding of those needs [10]. CE bridges the gap between technical and social approaches to infrastructure solutions by acknowledging that technical solutions must be socially appropriate for each community if they are to be sustained and supported. Coastal resilience is well suited to CE methodology due to the interplay of identity, value, capability, and need that governs each community's optimal approach.

### 1.1 Research Objective

The objective of this study is to improve the long-term sustainability of nature-based infrastructure solutions for shoreline stabilization in the Great Lakes region by combining standard technical engineering practices with QE techniques.

## 2 Methods

While most QE studies analyze data using Epistemic Network Analysis (ENA) [11], we employ a process that leverages the same strengths as ENA but approaches data analysis from the opposite direction. ENA quantifies and connects codes in a network model [12] while CE develops numerical relationships before qualifying them with interactive technology assessment in order to narrow the field of potential solutions. Our goal is to facilitate complex decision making [13] for engineers. Engineers are generally more comfortable with numerical data, so we can improve the decision-making process by converting their experiences and observations into numbers which they can then input into a decision matrix, a tool frequently used by engineers to make complex decisions. The result allows engineers and project managers to ultimately make an informed decision that is appropriate and sustainable for their community.

In our case study, we will partner directly with three community testbeds along the Great Lakes shoreline. Communities will be chosen based on varying size, economic conditions, and shoreline use to ensure that the methods are applicable for a diverse set of communities. Investigators following the CE methodology use a two-pronged, interactive approach that intertwines technical design with participatory QE.

The CE methodology (See Fig. 2) is described in detail in [14].

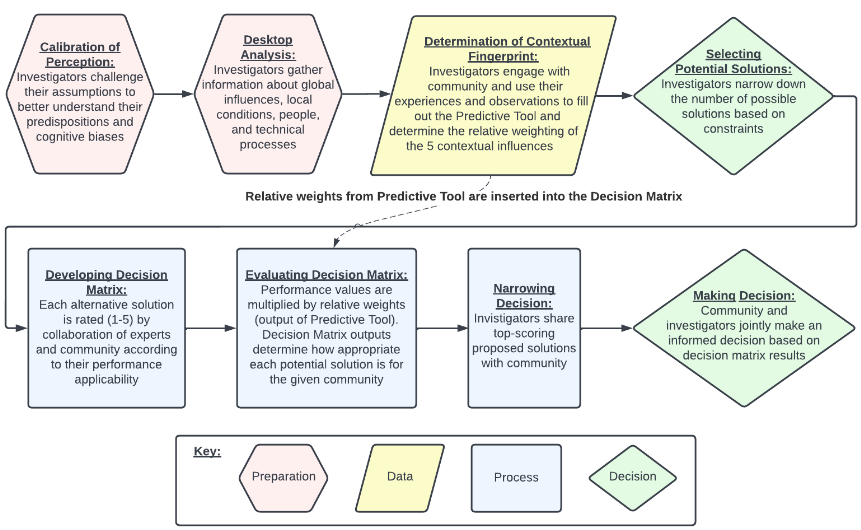


**Fig. 2.** The 8 steps of the CE process.

After we calibrate our perception and perform a desktop analysis, we will spend two to four months engaging with communities to weigh the 5 contextual influences—cultural, educational, political, mechanical, and economic—that affect the adoption, maintenance, and adaptation of infrastructure solutions, as defined in Table 1 [15]. In conjunction with community members, we will evaluate these influences using a Likert Scale of 1-5 on a 44-question Predictive Tool based on our experiences and observations. This tool transforms qualitative, ethnographic data into a quantitative representation of the relative importance, or weight, of each contextual influence for a community.

**Table 7.** The five contextual influences for adoption of new technologies

| Influence | What high value means | How it matters |
|---|---|---|
| Cultural | A commonly shared identity | Values associated with identity cannot be changed and must be adhered to |
| Educational | A desire for knowledge | New ideas and new processes may be welcome |
| Political | A power dynamic | Authority and social status must be acknowledged and respected |
| Mechanical | A facility to make things work | Comfort with familiar processes leads to acceptance and upkeep |
| Economic | An inability to meet needs | Cost will govern decision-making, income production will be important |

We will then have shoreline stabilization experts evaluate each proposed solution according to their performance on the 5 contextual influences. These performance values, along with the relative weights from the Predictive Tool will be inserted into the Decision Matrix (See Fig. 3). These weights will then be multiplied by the performance values for each proposed solution and summed to produce the output. The output represents how appropriate each potential solution is for the given community based on the ethnographic data collected and interpreted by investigators. Resultant output scores will be used to further narrow down potential solutions and eventually make an informed decision, with higher output values denoting a better fit.

| Potential Solutions | Implementation Cost (Economic) | Comfort with Use (Mechanical) | Breadth of Application (Political) | Design Comfort (Cultural) | Adaptability Evolvability (Educcational) | SCORE |
|---|---|---|---|---|---|---|
| *weighting* | Relative weights from Predictive Tool | | | | | 1 |
| Vegetation | Performance values determined by shoreline stabilization experts | | | | | Output |
| Edging | | | | | | |
| Sills | | | | | | |
| Breakwater | | | | | | |

**Fig. 3.** Example green infrastructure decision matrix for a community along the Great Lakes.

## 3 Expected Outcomes and Next Steps

This study will use the CE Predictive Tool to guide the selection and implementation of nature-based infrastructure solutions for coastal resilience in the Great Lakes region. This research expands on the application of QE and existing CE methods to empower systems of interrelated communities to make sustainable technical decisions to mitigate the harmful impacts of climate change. A future goal of this project is to develop an accessible, web-based infrastructure selection tool to allow land and water managers in the Great Lakes region to make educated decisions about climate resilience in their communities.

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# An Introduction to Open Network Explorer

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**Abstract.** As a continuation of previous work simplifying visualizations of ENA models for wider distribution, the Open Network Explorer (ONE) creates an interface between models and easily created visualizations. In this paper, we discuss the methods used for creation of this interface for sharing research data for quantitative ethnographic analyses, while (a) simplifying model details, (b) including example results and interpretations, and (c) allowing researchers to easily generate and publish them

**Keywords:** Sharing Research Data, Interface Design, Network Analysis, Quantitative Ethnography.

## 1 Introduction

With the continued pressure to publish more than results, researchers are presented with issues of interpretability, attendability, and complexity of the data, making it difficult to do so. These challenges have proven particularly difficult within the field of quantitative ethnography, which uses sophisticated modeling and visualization techniques to combine both quantitative and qualitative methods. In this paper, we discuss the continuation of prior work in the area of simplified ENA-based visualizations and a method which researchers can use to more-easily generate and publish similar versions themselves.

## 2 Theory

While there continues to be good reasons to share research data, many challenges still remain in the design and implementation of new approaches for sharing the results of complex data analysis. The Game of Thrones (GoT) interface [1] was not only well-received for its simplicity in describing and interpreting otherwise complex models and graphs, while connecting them to the underlying data, but also by researchers wanting to create similar interfaces for their own models.

However, prior implementations of simplified ENA interfaces have been limited to specific network models and the specific data used in generating them. Furthermore, the processes to create those interfaces, required a team of re- searchers, designers, and programmers. The Open Network Explorer aims to eliminate this requirement, streamlining the process such that the researcher can create, generate, and easily share publicly their model and corresponding visualizations.

The design decisions behind the Game of Thrones interface, as discussed by Swiecki and colleagues [2], intentionally left open the opportunity to create a tool researchers can use to create similar interfaces for their own research and models, which we continue here with the Open Network Explorer.

## 3 Methods

The Open Network Explorer (ONE) is a continuation of previous work designing the interactive interface for a study conducted on HBO's television series, Game of Thrones (GoT) [1], as well as taking important design elements from the epistemic network analysis (ENA) interface itself.[1]

After reviewing design choices in prior work, the procedure used in creating ONE involved a few steps: (1) abstracting the interface components from each other, (2) decoupling the interface from a technical backend or server and (3) defining a generic data structure for the interface.

First, although the interface, in its most complex form, has numerous components - a graph, plotting selections, data view, graph presets, and model summary notes - we wanted to allow these components to be used in any com- bination. The interface can be generated using only the plotting selection panel on the left and the graph view, creating a more simplified view, focusing on the network visualization. The same can be done, removing the left-panel, and only showing the data view on the right, or even further, removing all but the graph itself.

The next step was to create a stand-alone interactive page, not relying on a backend server (like the Game of Thrones interactive visualization using a hosted version of R) or an online service similar to ShinyApps [3]. There are a few benefits to this, namely it reduces complexity, lowers cost, and simplifies distribution. By creating a model visualization that is fully self-contained within standalone HTML file, the visualization can be hosted anywhere (e.g., GitHub), emailed to anyone and opened in a web browser, or even hosted by a journal alongside an article as an infographic or digital summary.

Lastly, the Open Network Explorer aims to be more than simply another visualization of ENA models. To do so, we had to create a general data structure, one not specific to a model created by ENA, or even within R, which has historically been used for most network visualizations with quantitative ethnography. To plot a model, whether it is an epistemic network, or a different type of network entirely, the only requirements are the existence of node positions, corresponding edge weights, and plotted point positions -

[1] ENA, a quantitative ethnography tool for constructing and visualizing networks using co-occurrences of coded data, was also used within the Game of Thrones study

all of which are optional (except if edges are supplied, then node positions would also be required).

## 4 Results

The interface, similar to the GoT interface, is divided into three main sections. On the left is the panel for selecting units or groups to plot. In the middle, the plots for the network graphs and their associated projected points. And on the right is a record of the data used to generate the models (see Fig. 1). Interested readers can explore an example of the interface by visiting epistemic-analytics.gitlab.io/qe-packages/vizena/.

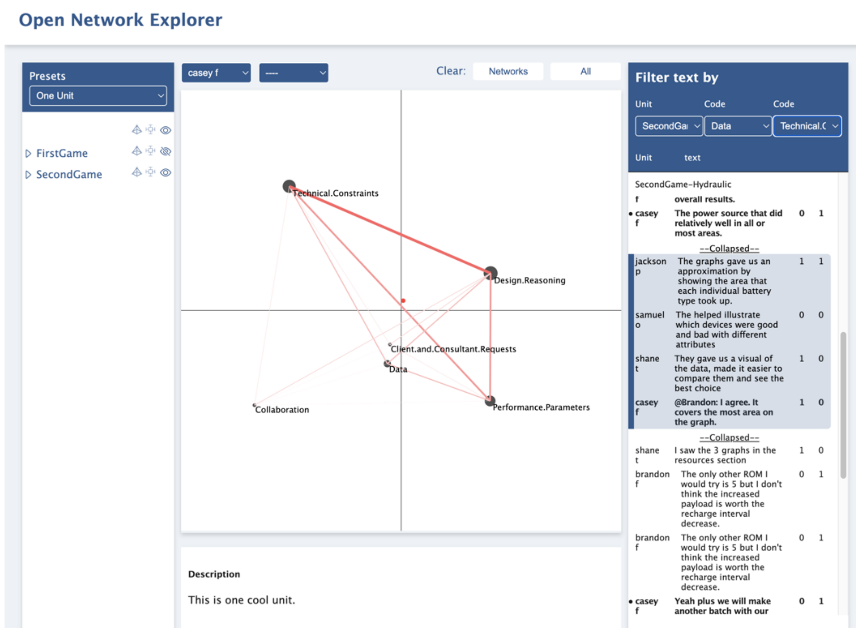


**Fig. 8.** An example of an Open Network Explorer interface.

To date, ENA representations are typically presented alongside relevant statistical information (e.g., the amount of variance explained by each dimension or the confidence intervals around a mean). While these aspects are important for researchers, they can be distracting and confusing for most other audiences. The interface itself has been simplified when compared to ENA and the Game of Thrones. Although an ENA model and its corresponding visualization(s) can be complicated - it is important for a researcher to easily, and quickly, create a ONE visualization - so there is a limited set of customizations to the interface that the user is allowed to make.

When generating a ONE interface, the researcher can include a set of pre- set units and groups of particular interest or significance within the model - including the corresponding network graphs. Further, for each preset, a narrative interpretation can be supplied to help users make sense of the results and scaffold their ability to understand the networks for other units and models. In addition to these presets, users can explore networks and comparisons, without narratives, for all units and groups within a given model.

Similar to prior ENA visualizations, ONE emphasizes the connection between the model and its underlying data - allowing the researcher to close the interpretive loop. [4] However, in contrast to the existing ENA tool [5] used to generate models, which emphasizes the model, ONE shows the model graphs right alongside the data, scaffolding the process of closing the interpretive loop. Users can even filter the data to show units and codes of interest (this is done automatically when using the presets feature), making the interpretations of the model and the connections to the data much more explicit.

## 5 Discussion

In this paper, we discussed the continuation of prior work in creating an interface for easily sharing quantitative ethnographic research data. In particular, our design attempted to address the challenges of creating a simplified interface for network models that is easier to disseminate than traditional approaches.

The considerations taken in the design allow the presentation of research data in way that addresses the potential lack of expertise and experience of the audience. By making it possible for audiences to easily see interpreted research data and interact with the data to verify those interpretations and produce new insights, the gap between the primary researchers and the audience is made smaller.

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# Examining Teachers' Discourse Around the Components of High-Quality, Effective Professional Development

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**Abstract.** Teachers' values, beliefs, and attitudes toward professional development (PD) have an impact on their learning, motivation, and performance. To successfully plan and implement PD, it is important for stakeholders to understand how teachers with varying beliefs make connections between the components of high-quality, effective PD. Using quantitative ethnography and epistemic network analysis, this study utilized forums on the social media platform Reddit to examine the difference in connection making between teachers positive and negative discourse about PD. Results from the Mann-Whitney U test showed no statistically significant difference in connections between the two groups. In both teachers' positive and negative posts, strongest connections were made between content focus and coaching/support, collaboration and coaching/support, and content focus and collaboration. Stakeholders should consider the strength of these connections when planning and implementing future PD programs.

**Keywords:** Teachers, Professional Development, Expectancy Values, Social Media.

## 1 Introduction

Despite the value of high-quality teacher Professional Development on both teaching practice and ultimate student success [1-3], most teachers associate PD with the workshop style, in-service training sessions mandated by their school, district, or state. Historically, these programs adopt a top-down approach "in which a district or school in an outside consultant or curriculum expert on a staff-development day to give teachers a one-time training seminar on a garden-variety pedagogic or subject-area topic" [5]. These homogeneous PD programs are often criticized by teachers for lacking coherence, continuity, and applicability.

In order to provide more well-constructed opportunities for learning, researchers have identified a range of principles, components, and characteristics of high-quality, effective PD [3, 6-11]. This study explores how teachers discuss their professional development experiences in terms of the seven features of effective PD identified by Darling-Hammond and colleagues [12], which have been proven to change teacher practices and improve student learning outcomes. This study employs quantitative ethnography (QE) and epistemic network analysis (ENA) to highlight the ways teachers describe and connect these features when discussing positive and negative past PD experiences. The findings from this study have implications for the planning and implementation of future professional development. The research question asks: *In what ways did teachers' positive and negative Reddit posts about professional development draw connections to the components of high quality, effective PD?*

## 2 Methods

Darling-Hammond and colleagues utilized a review of 35 methodologically rigorous studies to identify features of PD that were linked to change in teaching practices and student outcomes [12]. These served as deductive codes for the study (See Table 1).

**Table 8.** Codebook.

| Code | Definition | Example |
|---|---|---|
| 1. Content focused | Description of intended content focus of the PD (i.e., topic, curriculum, or practice); how chosen PD content is decided/negotiated; coherence with school/district initiatives | "My last PD was on writing proper assessment questions…" |
| 2. Active learning | Discussion of the application of active learning strategies in professional development contexts (e.g., observations, lesson planning or evaluation) | "I love when we go to a PD, and they make me a graphic organizer for my notes and they read me all the material." |
| 3. Collaboration | Discussions of PD that involves sharing ideas, collaborating in their learning in job embedded contexts, or participation in communities of practice | "... I did a whole year of awesome (real) PBIS PD with my alternative ed staff…and we learned from each other!" |
| 4. Models effective practice | Curricular models (i.e., lesson plans, unit plans, student work, etc.); Modeling pedagogical practices (i.e., peer observations, video cases, etc.) | "They claim that they're modeling.... My principal does the "if you can hear me clap once" thing at fac meetings...." |
| 5. Provides coaching and expert support | Discussion of instances in which teachers receive instructional coaching or other expert support; Emphasis on teachers' individual needs | "Differentiated PD sessions by teacher skill level." |
| 6. Feedback and reflection | Time to think about, receive input on, and/or make changes to practice through reflective practices or feedback | "Initial feedback was great!" |
| 7. Duration | Amount of time spent in the PD; Time to learn, practice, implement, and/or reflect; Time to allow changes in practice | "…it was only 90 minutes but it was basic training on a subject I already have passed..." |

Teacher reflections were scraped from discussion threads on two subreddits: r/teachers and r/education. The r/teachers community described themselves as “a sub for all things teacher related!”. Sampled threads were titled (1) “First day as a teacher and I am doing something called ‘professional development’” and (2) “What was your best professional Development?” The goal of r/education was to “provide a community in which educational stakeholders can participate in meaningful, reflective, and thought-provoking discourse about educational policy, research, technology, and politics.” Included threads asked (1) “Is Professional Development Wasting Your Time?” and (2) “Professional Development Idea?”

Posts were organized chronologically, then characterized as “positive” if they described: (1) interest and/or enjoyment in engaging in the PD, (2) the benefits of PD, (3) an understanding of the intent behind the PD, or (4) an appreciation toward PD. Posts categorized as negative included those who: (1) expressed annoyance toward engaging in PD, (2) used sarcasm, (3) considered PD to be useless, thoughtless, and/or a waste of time, and (4) did not see the benefits of PD. Posts that did neither were coded with “other” and subsequently removed from the network models to emphasize comparison between positive and negative posts. Socially moderated agreement was reached between two coders on the categorization of each post [13].

## 3 Results and Discussion

Epistemic networks visualized patterns of connection-making between posts with positive and negative discussions in relation to the seven characteristics of high-quality, effective PD. Despite differences in positive or negative affect across posts, all teachers in the forum tended to connect the same three components of high-quality, effective PD: (1) content focus, (2) coaching and support, and (3) collaboration (See Fig. 1).

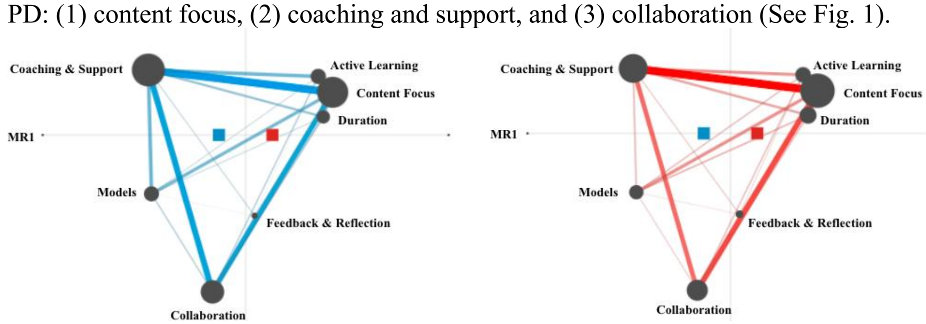


**Fig. 9.** Mean ENA networks for positive (blue, left) and negative (red, right) discourse around professional development.

Posts characterized as positive consisted of teachers describing professional development opportunities that were formatted in ways that could meet their individual needs (i.e., conference style), provided opportunities for active collaboration, and were led by those perceived to be experts in the field, which in many cases, were their own colleagues. Posts characterized as negative consisted of teachers sharing professional development experiences that were misaligned with their content area and/or grade band, insulted their level of subject area expertise, and failed to provide adequate opportunities to collaborate and learn from one another. These findings suggest that teachers value professional development that is: (1) aligned with their specific, socioculturally situated needs and interests, (2) delivered by experts in the field, and (3) provides ample opportunities for collaboration with colleagues.

Teachers who engaged in positive discourse around PD discussed the ways in which the focus of the PD was differentiated to support their needs, valued how their administrators sought feedback about the impact of PD sessions, and surveyed the staff regarding what topics they would like to see covered in future PD offerings. They also praised PD that was intentional and aligned with their curriculum, content area, or pedagogical practices, and valued peer collaboration as well as the ability to hear the diverse perspectives and experiences of their colleagues.

Teachers who engaged in negative discourse around professional development expressed frustration that the content they were being taught in PD had little to no application in their own classrooms. Teachers articulated how not only their individual strengths and areas of need were not accounted for, but also that the coaches and consultants hired to support teachers often had even less expertise than they did, making the overall PD experience feel like an insult. Teachers tended to critique both the materials addressed in the PD, and also the ways in which the materials were delivered, favoring resources and trainings offered by teacher peers. On the other hand, teachers described how some districts lacked the necessary staff or resources resulting in the burden of PD falling on overburdened or un-deputized educators.

## 4 Conclusion

In sum, while all aspects of high-quality, effective PD should be considered in the design of PD, teachers appear to connect and value content focus, coaching and support, and opportunities for collaboration most. Prior to engaging teachers in professional development, administrators should consider methods to better understand teachers' perceived areas of need and preferred learning modalities. Just as teachers are asked to differentiate instruction to meet the needs of their students, administrators should differentiate their professional development offering to address teachers' professional goals. It is imperative that the content focus of PD sessions align with teachers' subject area, curriculum, grades, and school context. Additionally, administrators must be cognizant of teachers' existing expertise, especially as it relates to content knowledge, as teachers find it insulting to listen to "watered-down" content about a topic they are already well-versed in. Professional development should also offer ample opportunities for collaboration, allowing teachers to engage in the co-construction of knowledge [3].

Future work will involve the examination of changes in teachers discourse around PD over time, a comparison of teachers' PD discourse across various social media platforms such as Facebook and Instagram, and an in-depth analysis of teachers discourse around the three components of high-quality, effective PD emphasized by teachers.

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# Epistemic Network Analysis used as Learning Analytics Visualization: A Systematic Literature Review

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**Abstract.** Epistemic Network Analysis (ENA) is a graphics-based analysis technique used in different fields by researchers aiming to model and visualize patterns in a given segment of discourse data. Recently, some researchers went beyond the analysis use and started to explore ENA as learning analytics visualizations. This paper presents a systematic literature review regarding the use of ENA as a learning analytics visualization in educational settings.

**Keywords:** Epistemic Network Analysis, Learning Analytics Visualizations, Systematic Literature Review.

## 1 Introduction

This paper presents a systematic literature review on ENA regarding its use as a learning analytics (LA) visualization to support instructors and students in their educational settings. In this work, we understand LA visualizations as a tool "where learners are given access to visual representations of their knowledge, activities, abilities, assessment outcomes, or any other analytics that have been performed within their learning context." [1]. By educational settings we mean "places that offer the educational services to students according to specific objectives." [2]. The educational settings considered were: pre-school, elementary school, middle school, high school, K-12, and higher education. A broader K-12 category was used to support classification when papers did not specify which grade level the research was completed. Our overarching research question is, "Is ENA being used as a learning analytics visualization to support instructors and students in their educational settings? If so, how is it being used?".

Previous reviews involving ENA were conducted by [3], [4], [5], and [6]. Kaliisa et al. [3] conducted a scoping review of 60 studies employing Quantitative Ethnography (QE) approaches to establish where the boundaries of QE might and should be to understand the field's identity. Porter et al. [4] performed a systematic review of the proceedings from the 1st International Conference for Quantitative Ethnography (ICQE) to discover some of the methodological decisions in those works. Zörgő et al. [5] aim to build a living systematic review of the work that is being done in the QE community to see the choices we, as a community of scholars, have made in research design and operationalization as well as how QE scholars have conceptualized QE. Elmoazen et al. [6] did a systematic review of ENA educational applications in empirical studies, looking for what ENA methods have been used to address educational applications and the main findings from those studies. As we can observe, previous works did not review ENA from the perspective of using it as a learning analytics visualization to support instructors and students in their educational settings.

## 2 Methodology

Our search was done during January 2022 and considered four databases and one proceeding: ERIC, JStor, Springer, ACM, and the Supplemental Proceedings of the International Conference on Quantitative Ethnography (SPICQE). The rationale for including those sources were: ERIC is an online library of education research and information, sponsored by the Institute of Education Sciences of the U.S. Department of Education; JStor contains full-text articles from more than 2,600 academic journals across the humanities, social sciences, and natural sciences; Springer is the editor of the International Conference on QE proceedings; ACM is the editor of the Learning Analytics and Knowledge Conference proceedings, where works on ENA are published; and SPICQE which includes the peer-reviewed posters presented at the conference.

We consider full papers, posters and short papers with at least four pages, peer-reviewed, written in English since 2017. This year was selected because this was the year Shaffer [7] wrote his book about QE and formally introduced ENA. We used the following keywords for our automatic search: "epistemic network analysis." We purposely did not include "visualization" in the keywords because we would like to retrieve all works done in ENA. After removing duplicates, we read all remaining titles and abstracts and skimmed through the papers to confirm that they are works that used ENA as a learning analytics visualization. From the 122 papers filtered, only seven used ENA as a learning analytics visualization.

## 3 Results

Five out of the seven works were used in the higher education educational setting. Of those five, four studies used ENA as a LA visualization for instructors, and one used as a visualization for a researcher. So far, no work has used ENA as student-facing LA. The result of [8], conducted in the literacy area, explored whether ENA could provide a useful pedagogical tool for teachers to support their assessment of longer student writing assignments and to visualize understanding of subject learning. In health education, Fernandez-Nieto et al. [9] used ENA to examine what insights teachers can gain from visual representations of nursing teams' spatial behaviors using ENA. Moraes et al's. [10] study in the collaborative learning area examined how ENA can be used for instructors as a visualization that unveils the connections that students are making in an asynchronous online discussion between the concepts being learned. Prieto et al's. [11] work on learning analytics used ENA to visualize LA data over a single user (a researcher), providing self-awareness on lifelong social-emotional learning. Vega's [12] study on pre-service teachers used ENA as LA visualizations to co-construct profound data interpretations with pre-service teachers during an interview where the researcher conducted participant member checking.

It is important to notice that we did find two other works that used ENA as LA visualizations. However, the first work, Herder et al. [13], did not explicitly mention in which educational setting the study was conducted. The purpose of the work was to use ENA to produce and visualize data about collaborative student activities to support teacher interventions in virtual internships. The second work, Nguyen [14], did not apply ENA in any educational settings considered in this systematic literature review. [14] work examined how participants on the crowdsourcing platform Amazon Mechanical Turk interpret quantitative ethnographic visualizations, with and without annotation for data uncertainty. It is interesting to observe that 13 of the 122 total papers found in our ENA search did not state in which educational setting the work was conducted; they just mentioned being used by teachers, students, or both teachers and students. We argue that it is crucial for papers to explicitly describe in which setting(s) the study was done, particularly if we would like to consider doing replication studies.

As we can observe, the majority of the papers were recently published (2021 and 2022). We believe that this is showing a trend in the future use of ENA as LA visualizations, as Shum [15] claimed in his keynote speech at the International Conference on Quantitative Ethnography'20 (ICQE'20) titled "QE Visualizations as Tools for Thinking." In his talk, Shum argues for a Knowledge Art Framework, where we should consider several aspects when designing visualizations with QE and ENA in mind, such as the choices we make for shaping a visualization, how our interpretation affects the stakeholders, what are the narratives behind those visualizations, how to interpret and adjust to unexpected results when sharing visualizations with participants.

While the work of [8] pointed out that ENA supports the teacher's understanding of subject learning, [9] claimed that one of the five teachers found the ENA visualizations very confusing and could not interpret them. This indicates that the use of ENA as LA visualizations needs to carefully consider the group of stakeholders that will use those visualizations, so those visualizations are helpful to them. Another important aspect is that ENA as LA visualizations are tools to assist instructors in assessing students' learning; they are not here to replace the teacher's assessment of student work, as also mentioned by [8]. In that sense, the framework proposed by [15] should be considered in works related to ENA as LA visualizations.

## 4 Limitations and Future Works

Our review is a preliminary work that used four databases and looked for a general understanding of how ENA is being used as a LA visualization in educational settings. However, we did not examine any specific pedagogical theories behind those visualizations nor discussed specific design choices behind QE and ENA. For future work we intend to expand the number of databases and do a complete analysis of those works considering what is proposed by Zörgő et al. [5].

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# Using ENA to Understand the Perceptions of Professionals, University Professors, and Graduate Students in the Computer Science Field Regarding the Development of a Machine Learning Program for Youth

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**Abstract.** Understanding the socioethical implications of machine learning (ML) is rapidly becoming a necessary competency, but it is unclear how to integrate such knowledge into K-12 educational programs. In this study, the interview discourse of a Computer Science (CS) industry professional, CS university professors, and CS graduate students were analyzed using QE with ENA to provide a grounding for the development of a ML program in K-12. These initial findings revealed that participants emphasized (1) integrating ML skills/knowledge with socioethical elements, such as minimizing bias and harm in algorithmic development and (2) the role of human interaction in algorithmic development.

**Keywords:** Epistemic Network Analysis, Machine Learning, Machine Learning Bias, Algorithmic Bias, K-12 Education.

## 1 Introduction

Machine learning (ML) technologies have created opportunities to improve the daily lives of everyone. Examples include automated driving or other smart technologies [1]. However, as advancements in ML technologies continue, so does the (re)perpetuation of systemic oppression and other socioethical issues, such as bias against communities of color in facial recognition systems and predictive policing algorithms [2]. With more research aimed at educating youth about ML and socioethical issues [3], there is a need to develop guidelines for the design of critical ML (CML) learning environments. CML educational programs are those that include technical and conceptual aspects of ML as well as the socioethical issues that surround these technologies [4]. Recent studies describe how to implement and assess ML content knowledge in K-12 curriculum [5-6] and educating youth on how algorithms can be biased [7]. However, there are limited studies that include stakeholder voices in computer science (CS) fields around developing a K-12 ML educational program focusing on socioethical knowledge. Thus, in this study, we explore the perceptions of industry, professors, and graduate students who employ ML in their work. This study serves as the first step toward providing a grounding for the development of learning standards and guidelines for a CML curriculum design. The study is guided by the research question: *What are the perceptions of CS professionals, university professors, and graduate students on youth education in ML?*

## 2 Data Collection and Analysis

The researchers conducted 9 semi-structured interviews with three university faculties in computer and learning sciences, 5 graduate students in CS majors, and 1 industry professional working at an international technology corporation and included open-ended questions, such as "What are your thoughts about youth learning about ML/AI?" The interviews were transcribed and segmented by turns of talk, producing a total of 540 lines of data. Codes were developed using an inductive grounded approach, deriving the codes from the data itself [8]. This resulted in 2 primary codes and 10 secondary codes: (1) *Knowledge* (Cohen's Kappa)**:** ML/AI Application (0.94); Limitations of ML/AI (0.89); Privacy (1); Human Involvement or Interaction (0.90); and Bias, Prejudice, and Harm (0.94); and (2) *Skills and Practices* (Cohen's Kappa)**:** Minimizing Bias and Harm (0.87); Assessing Motivations (0.91); Trust Building (0.88); Algorithms and Computational Thinking (0.94); and Training and Testing Machines Using Data (0.89). Two researchers developed the Codebook and then separately coded one-third of the lines to check for interrater reliability. The lines chosen were spread out evenly among all 9 participants and validated using Cohen's Kappa. The first author then coded the remaining lines. ENA [9] was used to analyze the interview discourse of each participant. Using a sliding window [10] of 4 lines of talk (one line plus the preceding 3 lines), researchers were able to count and visualize the co-occurrences of codes, demonstrating the connections each participant made when discussing the various themes associated with the codes. ENA networks were produced for professors, graduate students, and industry in order to model how each group conceptualized ML education for youth.

## 3 Results

Graduate students emphasized the need to educate youth regarding ML skills, *algorithms and computational thinking* and connecting these skills to knowledge regarding the role of *human interaction* as evidenced by the thick lines connecting these codes (See Fig. 1). The ENA network for graduate students demonstrates many connections between *knowledge* codes (bias, limitations of ML) and codes representing *skills* (training and testing machines, assessing motivations) although these connections are not as strong as the ones connected to *human interaction/involvement*. All codes in this network form some sort of connection with *human interaction*. An example of connecting skills to human involvement is demonstrated when Cane, a graduate student, stated:

> You can do two models based on two different sets of training data and you can show them, 'Hey, do you see how this one outputs basically bias and incorrect answers, whereas this one with the more representative training set does make better decisions

that more humans would make?' And then, it also shows them that AI aren't perfect impartial beings.

Here, Cane is connecting *training machines using data* with the knowledge of biased output, alluding to the effect of *bias* on humans through representation (or lack thereof).

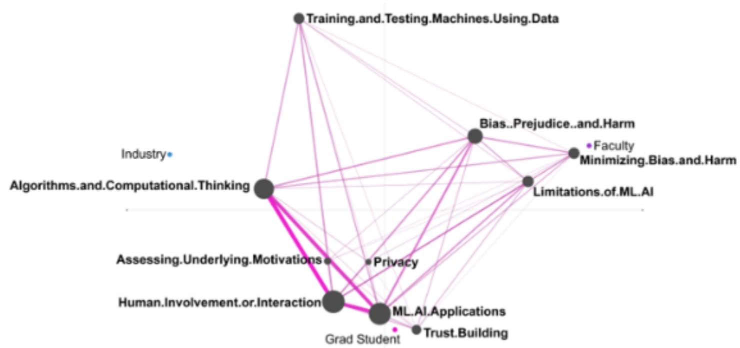


**Fig. 1.** Discourse network for graduate students**.**

The discourse network for the industry professional was similar to the graduate students' network in that it showed a strong connection between *algorithms and computational thinking, human interaction and ML* (See Fig. 2). This network also showed every code connected to *human involvement or interaction*. For example, Timothy, an international tech researcher, said:

ML is algorithms that are trained on data and the data has to come from somewhere. And so there's the ethical questions around where does the data come from? And there are ethical questions of when someone's going to use this algorithm, this model.

In this statement, Timothy stressed educating youth about algorithms and training data, *human involvement* in data input, and the ethical implications of algorithmic use for humans.

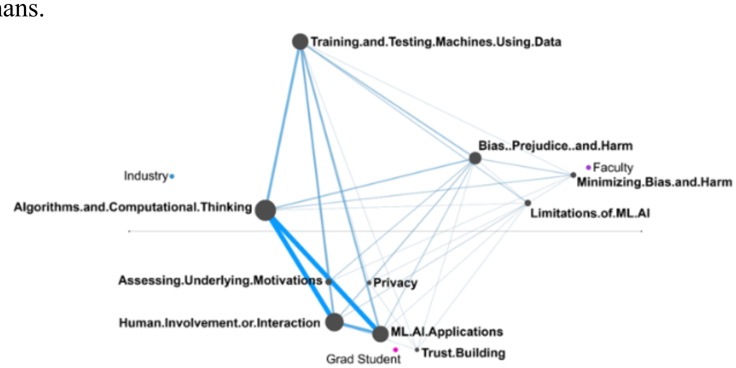


**Fig. 2.** Discourse network for the industry professional.

The ENA network for the university professors showed equal connections between all of the codes representing both knowledge and skills (See Fig. 3). Again, *human involvement or interaction* was connected to every code in the network, demonstrating an emphasis by professors in this group on the role of humans in ML/AI. When one professor, Keaton, was asked about their opinion regarding youth learning ML concepts and the potential ethical and social implications of ML technologies, he said:

> So that would be the first step, the ontology part of it. How do these things come to be? And then the output part of it, what are the potential impacts that again, it reminds me of working in labs with science kids. “Okay. So here's this thing. What could go wrong and how are you going to mitigate that? And if it does go wrong, what do we do, right?” Those are the questions that have to happen before you start even using basic glassware in a science lab. And so I think that those are the conversations that need to happen, that these need to be treated as complex and potentially damaging tools.

Keaton discussed *computational thinking* when relating how he would teach ML concepts to youth, as shown by the mention of computational factors such as input and output. Additionally, Keaton connected *computational thinking* to *bias, prejudice, and harm* and *minimized bias and harm* when comparing ML education to laboratory safety and how to train youth about the dangers of these technologies.

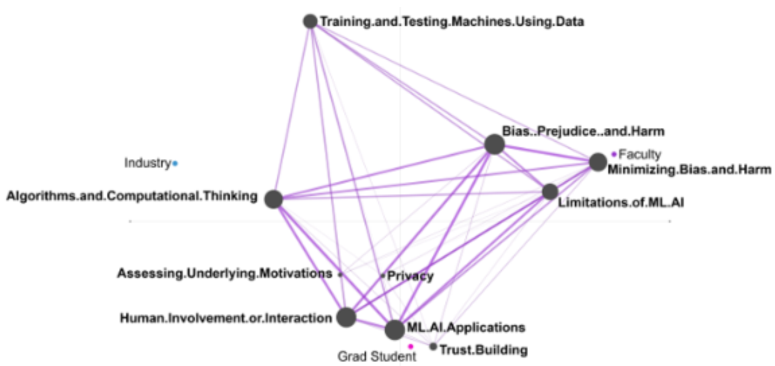


**Fig. 3.** Discourse network for university professors.

## 4 Discussion and Conclusion

The discourse networks of the graduate students, university professors, and industry in CS fields demonstrated that these participants valued skills/knowledge of ML (algorithms and computational thinking, training and testing data) and the socioethical issues associated with ML (recognizing and minimizing bias, prejudice, and harm). Furthermore, professors, graduate students, and industry participants in this study connected socioethical issues and ML skills/knowledge to human involvement and interaction, suggesting the importance of youth understanding the role of humans in creating algorithms that minimize bias and harm to others. Integrating both skills/knowledge with socioethical components in ML programs in K-12 could promote youth being responsible users and designers of ML technologies in the future. Limitations of this research include having a small data sample from 9 participants. Forthcoming research needs to extend to interviewing teachers, K-12 students, and community members in order to gather more diverse feedback on elements of a youth ML educational program that would be important to stakeholders and include aspects that are important to specific contexts.

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# Impact of Affect on Self-Regulated Learning

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**Abstract.** The study explores the influence of various affects on self-regulated learning (SRL) behaviors in a learning environment. The ENA models visualized how the affective states of confusion, delight, engagement, and frustration impacted the connections between SMART codes (Searching, Monitoring, Assembling, Rehearsing, and Translating) as the SRL framework. The log data, with integrated affect detectors, was coded for SMART. The findings show that Frustrated and Confused learners shared similar actions of Searching with Monitoring and Assembling, respectively, implying attempts to shift from cognitive disequilibrium. Engaged Concentration was linked to Translation actions; Delight with Searching and Monitoring after resolving an issue. Further investigation is required on the role of affect in SRL learning for better support.

**Keywords:** Affect, Self-Regulation, Computer-Based Learning Environment.

## 1 Introduction

Self-regulated learning (SRL) has been established as an essential skill that improves student learning [1]. Recent studies show techniques to detect SRL behaviors in computer-based learning environments (CBLE) using log data [2-3]. The role of Affect in SRL [4-5] has been acknowledged; however, its impact is not yet clearly known [6]. Thus, it is useful to explore this connection to advance theory and improve system design for SRL support. Winne and Hadwin's COPES [7] model that defines cognitive operations of searching, monitoring, assembling, rehearsing, and translating (SMART) is used as a theoretical framework for SRL. This study explores how various affective states of learners – Confusion (CON), Delight (DEL), engagement (ENG), and frustration (FRU) – influence the SRL behavior through the SMART model [7]. The action log data is used with detected affects [8], and real-time student interview data.

## 2 Methods

Data was collected from 98 sixth graders in a mid-southern U.S. school science class in 2016–2017 using an open-ended CBLE, Betty's Brain, based on the learning-by-teaching paradigm [9]. Learners make decisions on how to teach "Betty" (parsing through sources, taking quizzes, or seeking virtual support) and draw concept maps, which demand high SRL skills. Real-time affect detectors were used that were already integrated with the software [8], which also prompted student interviews. Interview data is not used in ENA models, but only in closing the interpretive loop. The deductive codes were based on SMART schema [7] for SRL that were used on action log data[1]. The original codebook from [10] was revised with 2 new codes, and each relevant action had been mapped to a corresponding SMART behavior. The actions that were repetitive or irrelevant were dropped. The operationalization of SMART codes [10] is given in Table 1.

**Table 9.** Codebook of SMART operations

| Code | Definition | Example |
|---|---|---|
| Searching | Learners focus their attention on a knowledge source to update their working memory. | Search the virtual textbook, search teacher guide action |
| Monitoring | Learners evaluate their perceptions compared to available standards. | Reviewing quiz feedback, deleting causal link |
| Assembling | Learners connect new knowledge items to networks of prior knowledge; strengthening working memory. | Adding a concept or a causal link to the map |
| Translating | Learners reformat information into a new representation, creating the potential for alternate interpretations. | Taking notes about readings, converting text to a causal link |

A total of 57,433 action-level entries were coded as one of the SMART categories using a binary approach of 1 or 0 for the occurrence or non-occurrence. No rehearsing action was logged in the platform, so this category was not coded. Action-level logs also had corresponding detected affect. The conversation variable was chosen as the User (i.e., the student) so that no associations were made between different students' action log. The Unit variables were set as the Affect and the Users. A moving stanza window of 10 was selected based on the average time duration across actions.

## 3 Results

The ENA model (See Fig. 1) showed differences in affect groups (Mann-Whitney U tests with 0.97 and 0.98 values for x and y-axis) based on the position of means. The three categories emerged with ENG, DEL, and CON and FRU. CON and FRU had closer means with similar student actions, which aligns with previous literature that shows that confusion leads to frustration if not resolved [11]. Figures 2, 3, 4, and 5 show ENA networks for CON, FRU, DEL, and ENG corresponding with connections between SMART codes.

These ENA models show that learners when confused, relied heavily on Searching with Monitoring behavior (0.64). Confusion follows the state of cognitive disequilibrium [12] that can also contribute to a shift in SRL states [6]. The mean located towards Searching shows that students are trying to fill gaps in their knowledge and activate existing information to shift towards cognitive equilibrium, as found in interviews: "I

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1 Each action item mapped to SMART category: https://docs.google.com/document/d/1gs6KOSApFQIJyqkb-yJP5kdyoRTTdHv4e5r6-f1BVoM/edit?usp=sharing

am trying to see what is happening here. [causal links]" and "I need to find that information." Frustration model is pulled towards Searching and Assembling, implying that awareness of frustrated learners about their own state of knowledge pushes them to assemble i.e., to add a useful chunk of information, and create links, to resolve their issue. Snippets from interviews below explain how student searches to assemble new information after monitoring their knowledge gaps: "When I get frustrated, um, [I] think of what I did wrong. And like, how could I make it more complicated (the concept map) with new information."

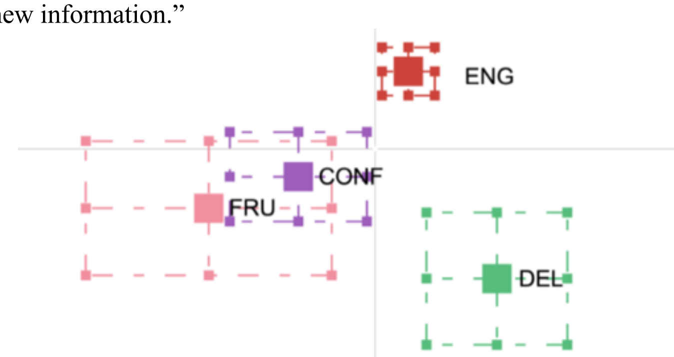


**Fig. 1.** ENA model displaying means and confidence intervals of all affects.

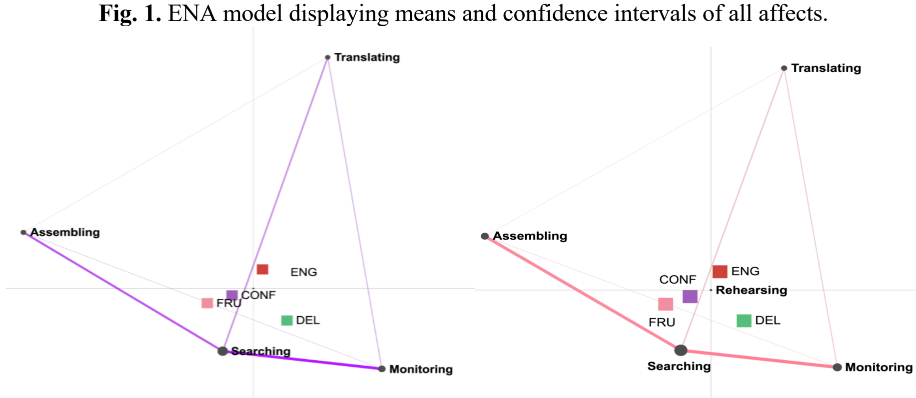


**Fig. 2.** ENA models for confusion (CON) (left, purple) and frustration (FRU) (right, pink) with SMART codes.

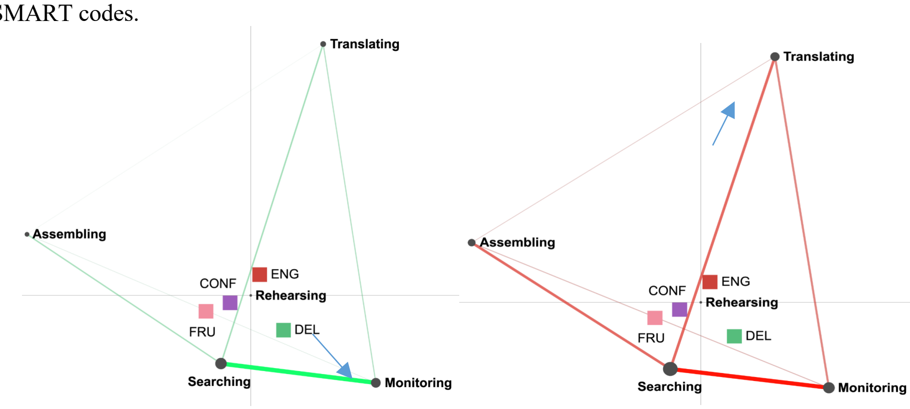

**Fig. 4.** ENA model for delight (DEL) (left, green) and engaged concentration (right, red) with SMART codes.

Delight is a rare affect to observe (3% of total) and shows a strong connection (thrice as strong as the next one) between Monitoring and Searching (0.71). Interviews highlighted that students were delighted mostly because their solution worked, or some strategy that they tried showed results, so they carefully monitor the outcomes. Lastly, Engagement was the most common state (80% of the total), which is in alignment with previous research [13]. The mean is pulled towards Translating, and the model shows strong connections to Translating with Searching (0.42) and Monitoring (0.32). This is unique to engagement and reflects how learners in this state transform their knowledge into multiple representations, as this interview shows: "I am answering more MCQ, checking results."

## 4 Discussion

The study shows that confused and frustrated learners show similar action patterns, and engage in Searching primarily, with Monitoring and Assembling, to shift their state of cognitive disequilibrium. Engagement facilitated learners to display the cognitive behavior of Translating, and learners were Delighted after finding a solution via Monitoring. There remains a risk of spurious associations due to platform design restricting or promoting certain kinds of actions leading to an unbalanced dataset (as observed here with no actions for rehearsing, whereas 58.6% of actions coded for searching). It also emphasizes that Betty's Brain facilitates learners to engage in cognitive behaviors of Searching and Monitoring more easily and frequently than others. This work requires further investigation to explore the nuances of the types of each affect, its duration, and the next transition to understand the connections with SRL more deeply. It has implications for improving system design and offering personalized scaffolds to develop SRL in learners.

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# Examining Community Development in an Online, Global, Collaborative, Learning Environment

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**Abstract.** Literature on online education settings indicates that engagement, collaboration, trust, and shared goals are fundamental factors for community development. This paper examines how community develops among adolescent students in an online, collaborative, informal STEM-focused learning environment. Transcripts of discourse from four video conference calls, known as online global meetups in this community, were examined using Epistemic Network Analysis (ENA) to identify key patterns related to community development amongst the students. Findings show changes in the patterns of discourse corresponding to the development of community over two time periods in 2021. In the first time period (February to March 2021), the models depict a shift towards more vibrant and varied discourse, and in the second time period (October to November 2021) the models showcase a shift from social-oriented interactions to more substantive, content-related discourse. These observations demonstrate how community develops and drives the discourse patterns in this online, global, collaborative, learning environment.

**Keywords:** Community, Collaboration, Learning, Global, Virtual, Online.

## 1 Introduction

The landscape of online education has been transformed by the constant evolution of new technology. More recently, the unexpected and urgent impact of the Covid-19 global pandemic has launched a new wave of online learning. As online and hybrid models become the new norm even as the Covid-19 pandemic restrictions begin to ease, the education community must consider the impacts of this shift for future online learning environments. One key component that risks dilution within an online setting is a sense of connection and engagement amongst group members—the community.

Rovai [5] describes a learning community as a process of four components: spirit, trust, interaction, and a shared expectation of learning. Spirit includes areas such as cohesion, membership, and friendship that allow students to equally support and constructively challenge each other. Trust refers to the confidence in members to rely on others as well as a genuine concern and interest for one another. Interaction can be driven by a goal of task completion or by socioemotional factors, including sharing of personal information or empathetic engagement. Lastly, members of a classroom community must hold a shared belief that their learning needs are being met through their involvement in the program [5].

Brown [2] determined that the process of community development occurs in three distinct levels. First, learners make online acquaintances by finding individuals with similarities. Learners then contribute to the community to establish membership. Lastly, learners reach the final level of comradery, which is achieved through long-term or repeated association with others via personal communication [1].

Utilizing Rovai's [5] framework, Espino et al. [3] demonstrated community development in an informal, online, learning environment across an eight-month timeframe in 2017. Adolescent learners in this online network began their interactions by sharing personal information to build comradery and foster spirit of membership. Interactions were qualified as task-driven encompassing STEM projects and presentations, while prosocial interactions built a sense of trust that allowed for substantive comments and a willingness to seek clarification about the content of focus. Across the eight-month timeframe, these discourse patterns increased in strength to signify a greater development of community over time.

The present study aims to expand the previous work by Espino et al. [3] layered against Brown's levels of community development [2] by analyzing the same adolescent learning environment across a new post-pandemic time. This paper seeks to examine how community develops among adolescent students in an online, informal learning environment referred to as IC4 (International Community for Collaborative Content Creation). Student participants hail from over four continents to participate in collaborative multimedia projects on self-selected STEM-focused topics. Each week, students have the opportunity to share their projects and teach their peers via a synchronous video conference call, referred to as an online global meetup. These online global meetups allow the students to expand their knowledge about STEM topics and multimedia creation while simultaneously developing a sense of community.

## 2 Methods

The data analyzed in this study consists of four online global meetups: the first two took place in February and March 2021, and later meetups in October and November 2021. The February and March 2021 meetups included 12 and 11 participants from three countries: U.S., Kenya, and Mexico. The October 2021 meetups included 14 participants from five countries: U.S., Kenya, Mexico, Brazil, and Russia. The November 2021 meetup had 19 participants from U.S., Kenya, Brazil, and Russia.

Each online global meetup was transcribed and reviewed separately by two researchers. Across these four meetups, a total of 546 utterances were coded independently by two raters who followed a process of social moderation to reach final consensus on the coded data [4]. After the social moderation process, the coded data was uploaded to the Epistemic Network Analysis (ENA) webtool for analysis and visualization [6]. For this analysis, a participant's utterance was defined by a change in speaker and the separate meetups were defined as the conversations in which connections were limited.

**Table 10.** Codebook of constructs used in this analysis.

| Construct | Definition |
|---|---|
| Content Focus | Related to academic subjects or content |
| Inclusive Disposition | Encouraging participation of specific individuals in discussion |
| Social Disposition | Demonstrating pro-social tendencies |
| Collaborative Disposition | Promoting cooperation between two or more individuals |
| Information Sharing | Sharing of information on subject-related or technical topics |
| Participatory Teaching | Helping others to learn subject matter by providing factual knowledge |
| Feedback | Communicating one's feedback, suggestions, or opinions |
| Curiosity | Seeking clarification, elaboration, or further information |

## 3 Results

The subtracted ENA network models examining the students' discourse patterns in February 2021 and March 2021 global meetups can be seen in Figure 1 (left). Initial examination shows that the March 2021 network has a more vibrant network and varied discourse as compared to February 2021. The subtracted ENA network models examining student discourse patterns for meetups in October 2021 and November 2021 are seen in Figure 1 (right) and shows that the October 2021 network model is more oriented towards the left and November 2021 is oriented towards the right.

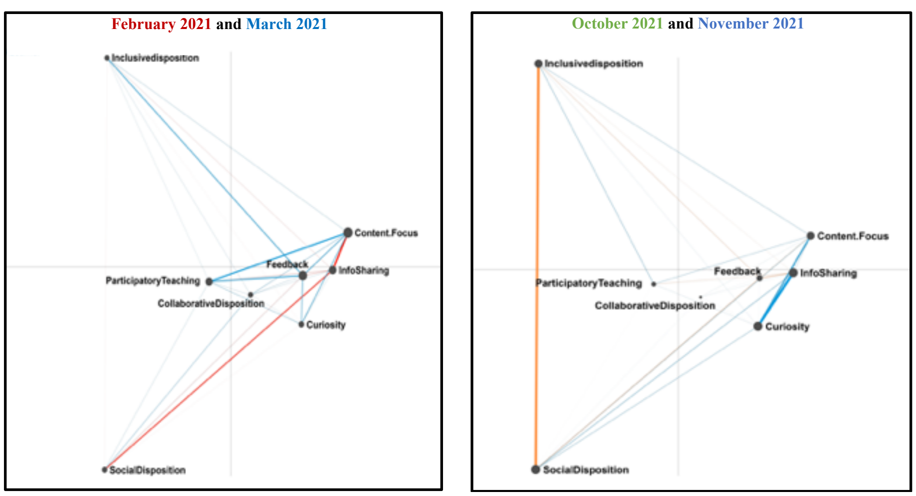


**Fig. 1.** Subtracted ENA network model of February 2021 and March 2021 (left) and subtracted ENA network model of October 2021 and November 2021 (right).

## 4 Discussion

The initial examination of the four global meetups gives insight into how community develops in an online, global, collaborative, learning environment. In the February 2021 meetup, the discourse was strongest surrounding Inclusive Disposition, Info Sharing and Social Disposition. The March 2021 meetup carried similar patterns but demonstrated more vibrant connections related to Participatory Teaching and Curiosity. The greater richness of discourse in the March 2021 meetup may be explained by two students who presented on similar topics in each meetup, which elicited an engaged discussion during the second meetup. This pattern exemplifies the first two levels of Brown's [2] research findings of shared interest and contribution.

Looking next to the Fall meetups, the ENA models depict a more significant directional shift and vibrancy in discourse patterns. The October 2021 meetup reflects discourse among student learners that was strongest between Inclusive Disposition and Social Disposition constructs. The November 2021 meetup shifted significantly to the right towards Content Focus, Info Sharing, Participatory Teaching, and Curiosity. The shift reflected between the October 2021 and November 2021 meetups may be explained by two student learners from Brazil who were present in both meetups. Looking again at levels of community development [2], the shared culture between the two Brazilian students can explain the connection that allowed for more engaged discourse during the second meetup.

### 4.1 Limitations

The results presented in this study have notable limitations. First, the individual participants present in the global meetups are not consistent over time. Secondly, the meetups used in this analysis cannot be generalized to a wider range of timeframes. Lastly, the researchers also acknowledge that culture is an additional element that plays a key role in community development in any contextual setting.

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# The Qualitative Network Approach (QNA)

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**Abstract.** Networks are a powerful tool to help understand and model human psychology. However, existing approaches preclude explorative, mostly inductive endeavors. For example, the network approaches that are popular in psycho metrics first require knowing which indicators to collect data for; and Epistemic Network Analysis, an approach for qualitative data, requires prior knowledge as to the meaning of code co-occurrences, how to sensibly segment data, and to interpret the results of the applied data reduction procedures. In this contribution, we introduce a qualitative network approach, implemented in the Reproducible Open Coding Kit (ROCK). This approach enables directly coding relationships (of deductively or inductively specified types) between codes in qualitative data, yielding a visual representation of those codes and how they relate to each other.

**Keywords:** Qualitative Methods, Networks, Methodology.

## 1 Network Models

Network models have become an increasingly popular means to study human psychology. They have been introduced as a psychometric tool [1] as well as a tool for analyzing qualitative data [2]. Each has specific strong and weak points. In the present contribution, we introduce a new method: a qualitative network approach.

In quantitative research, network models are commonly used to estimate psychometric networks. The nodes often correspond to indicators, such as items in a questionnaire (e.g., self-reported psychopathological symptoms or attitudes). The verisimilitude of the resulting network hinges upon how well the chosen indicators reflect psychological regularities (cf. [3]). Careful development and curation of the set of indicators therefore becomes a primary concern. However, this task has to be completed before data collection becomes possible (e.g., questionnaire creation requires knowing what to measure). This deductive approach means that it is hard or even impossible to discover omitted nodes, or to discover that the way psychological regularities have been delineated into indicators and nodes has low verisimilitude. This powerful method for confirmatory research does not lend itself well to the exploratory research that typically precedes it.

Collection and analysis of qualitative data does lend itself well to such formative work. Here, Epistemic Network Analysis (ENA) is often used to visualize co-occurrence patterns in sets of codes as applied to qualitative data. As these codes can be developed inductively, this approach works well for exploratory research. However, for ENA to make good on its eponymous epistemic inferential chain, a number of conditions have to be met. First, code co-occurrence must allow inferences about the phenomenon under study. In other words, ENA requires a plausible a priori model that describes how the phenomenon of interest is responsible for those code co-occurrences. Second, because the way the data are segmented determines when codes can co-occur, segmentation also requires sufficient knowledge of the data-generating process, such as relevant theory and psychological models (e.g., regarding memory, attention, and information processing). Third, the researcher has to be able to interpret the results of the data reduction procedures applied in ENA (e.g., means rotation) in terms of the relevant theory and phenomena of interest. To meet these conditions, researchers re quire substantial prior knowledge of the phenomena of interest. Therefore, strongly inductive, exploratory approaches tend to not lend themselves well to ENA, either.

Furthermore, in existing quantitative and qualitative approaches, the edges in the network either all represent the same type of relationship, or multiple types without distinguishing which edge represents which relationship type. They require that the re searchers have a theory as to how the phenomenon of interest manifests in the collected data in a way that, through the employed analytical procedures, allows epistemic inferences from the produced networks. Neither procedure can at present infer different types of relationships from the data: correlations or code co-occurrences are always assumed to be the product of a single data-generating process, precluding modeling a combination of, for example, causal, temporal, structural, and semantic relationships.

## 2 The Qualitative Network Approach (QNA)

The qualitative network approach we present here allows fully inductive mapping of networks using qualitative data, replacing the various auxiliary assumptions required by Ising networks and ENA with the assumption that the coders are able to discern the relationships of interest in the data. The approach consists simply of the concept of coding relationships, which is a more general case of conventional qualitative coding approaches: a methodological superset. Figure 1 shows a fragment of qualitative data coded with a small network as well as the resulting network as produced by the R `rock` package function `rock::parse_source()` (code at https://osf.io/nj4qc).

Network codes have three or four parts: the two codes and the type of relationship and an optional relationship weight (if relationship weights are not specified, either all edges will have the same thickness, or they can be computed as a function of the frequency with which the corresponding relationship was coded). To illustrate this, let us look at the first code in Figure 1: `[[tired->cranky||causal_pos||1]]`.[1]

[1] The code identifiers (here: "`tired`" and "`cranky`") and the relationship type identifier ("`causal_pos`") must start with a letter and only contain letters, numbers, and underscores.

This indicates that the coder decided that the data fragment justified inferring that in the participant's representation of the world, being tired causes crankiness. A second type of relationship was coded in `[[cranky->mood||structural||1]]`, expressing the coder's decision that the participant considers being cranky a part of their mood. In this example, structural relationships are visualized in blue.[2]

```
When I'm tired, I often get cranky. [[tired->cranky||causal_pos||1]]
In general, such things matter for my mood. [[cranky->mood||structural||1]]
For example, when I'm hungry, I also get cranky. [[hungry->cranky||causal_pos||1]] [[hungry->cranky||causal_pos||1]]
And when I have coffee, I feel cheerful. [[cheerful->mood||structural||1]] [[coffee->cheerful||causal_pos||1]]
But that's also because it's a drug I think. [[coffee->drug||structural||1]]
And coffee also makes me feel less tired of course. [[coffee->tired||causal_neg||1]]
My mood is also influenced by the weather. [[weather->mood||causal||1]]
Actually, the weather also matter for how hungry I get. [[weather->hungry||causal||1]]
For example, if it's very warm, I get much less hungry. [[warmWeather->weather||structural||1]] [[warmWeather->hungry||causal_neg||1]]
```

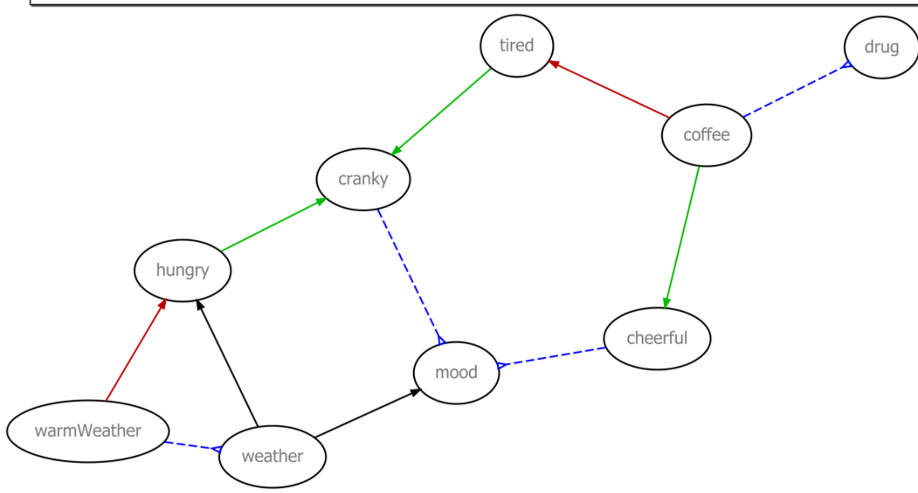


**Fig. 10.** A qualitative data fragment coded with network codes and the resulting graph.

## 3 Reevaluating Qualitative Coding Conventions

In qualitative research, the process of coding simultaneously organizes the data and shapes the researchers' thinking and theorizing. Ultimately, the produced code structures are often presented as a concise summary of the study's results: these code structures efficiently show which patterns were observed in the data.

Conventionally, such coding often occurs in code structures that are hierarchical (i.e., with a tree of nested codes) or flat (i.e., without relationships between codes; a special, constrained, case of hierarchical code structures). The chosen organizational mode imposes what one could call an epistemic hammer (cf. Kaplan's Law of the Instrument [4]). If codes are organized in a flat structure, the researcher is less likely to observe hierarchical relationships between codes. If codes are organized in a tree structure, such relationships become a fundamental tool in thinking and theorizing about the

[2] The colors and other edge aesthetics are included in the source file in YAML by specifying Dot attributes for each relationship type identifier (see https://osf.io/nj4qc).

data. In other words, the organizational mode in which codes are structured both facilitates the researchers' epistemic aims and constrains them.

As flat code structures are a special constrained case of hierarchical code structures (i.e., without actual nesting, so placing all codes in the root), hierarchical code structures are a special constrained case of network code structures: every code has exactly one parent, and all relationships between codes have the same nature.

When considering hierarchical code structures from this broader perspective, three things become apparent. First, although nesting (e.g., a code falling under its parent or in a theme) represents the same type of relationship in the entire code structure, re searchers typically do not specify what type that is. Often, nesting appears to suggest some sort of more precise specification of the concept captured by the ancestral code, but researchers generally do not explicate this (e.g., reporting standard JARS-Qual makes no mention of describing what code nesting represents [5]).

Second, when viewing hierarchical code structures as one of several organizational modes, it becomes apparent that selecting a hierarchical code structure is a decision: an exercise of researcher degrees of freedom [6]. Potentially quite an influential exercise, as the associated constraints also shape the researcher's thinking by nudging them towards construing the results in terms of clusters and subclusters (and as relationship type cannot be coded for each relationship, with cluster membership representing the same type of relationship). Nonetheless, researchers seem to take a hierarchical code structure for granted, not realizing this represents a decision with nontrivial epistemic consequences, a state of affairs again represented in reporting guidelines [5].

Third, when parsing network code structures, typically unique networks emerge for each coded data source. Merging these into one code structure requires many decisions that are often not straightforward. When researchers code with hierarchical code structures, they often work with a single code structure for all sources, causing them to make those same decisions in a less explicit manner. This makes it difficult to retain an idiographic perspective.

In conclusion, this qualitative network approach (QNA) represents a novel method for analyzing qualitative data, with a unique epistemic profile hitherto unavailable. It casts a new light on conventional approaches to code qualitative data and enables exploratory research to inform quantitative network approaches.

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# Augmenting Qualitative Coding with Machine Learning

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**Abstract.** This works seeks to augment the qualitative coding process by lever aging the relative strengths of the nCoder software package with machine learning. Multiple ways of structuring a Naïve Bayes classifier are tested against nCoder output for optimization. This classifier is then used show areas of outperformance over traditional techniques suggesting the future inclusion of machine learning methods when coding data.

**Keywords:** Machine Learning, Qualitative Coding, Naïve Bayes.

## 1 Introduction

The field of quantitative ethnography, QE, is concerned with achieving a deep understanding of the cultural discourse of a group, and one of the main tasks with this form of analysis is coding data for the presence of themes which represent the central ideas being discussed in a community of practice. To achieve this, tools such as nCoder [1] use a training subset of the overall data to derive a set of patterns which is then applied to the whole data. This is closely related to the common classification task within ma chine learning. However, a problem arises in that data sets used within QE are initially unlabeled (i.e., not coded) and thus unsuited for supervised machine learning approaches. Leveraging the strengths of nCoder in efficiently coding data through base rate inflation and Shaffer's rho as well as dividing the data in training and test sets, allows for the introduction of supervised machine learning techniques. To test the efficacy of using machine learning, a Naïve Bayes, NB, classification approach will be used. This technique is suitable as many patterns are contained within a single word thus keeping with the central assumption of conditional word independence. The NB classifier also has the advantage of utilizing the class conditional word probabilities which can use more information than a single text pattern. This may help overcome drawbacks with the nCoder pattern matching approach in that it is potentially susceptible to overfitting if the list of patterns is too specific to the training set as well as there being no guarantee the patterns will be similarly manifested in the test set. This presents the possibility of incorporating supervised machine learning techniques to improve the classification of text data within the context of a quantitative ethnographic approach.

## 2 Methodology

### 2.1 Data

The data set consists of user generated text data scraped from online forum discussions of the Social Security Disability Insurance program in the United States. For the purposes of this work, the code consists of the presence of discussion about the forms and medical evidence which are necessary for documenting and proving a qualifying medical condition for SSDI benefits. The code was developed using nCoder with a Cohen's $\kappa > 0.90$ and Shaffer's $\rho(0.90) < 0.05$ between a human rater and nCoder. As part of developing the code, 3,000 segments of the overall data set were randomly sampled which also served as the training data set for the NB classifier. The remaining data was used as the test set (110,602 observations) for comparing nCoder and NB classification predictions.

### 2.2 Determining Optimal Classifier

To select the best NB classifier, a series of experiments are conducted to determine the optimal approach. The parameters to be tested include using post-processed text data, Laplace smoothing, document term weighting, and utilizing n-grams. The raw user generated text was used as a basis for comparison against adjustments to the NB classifier. Post-processing of the text includes lemmatizing words as well as removing stop words and non-letter characters (i.e., numbers, special characters, etc.). Laplace smoothing is a technique allowing the assignment of non-zero probabilities to words/n-grams in the test set that are not represented in the training set. Properly adjusting the smoothing parameter has been shown to increase classification performance of the NB approach [5]. This is an important parameter to incorporate as there are many more words/n grams in the test set compared to the training set. Additionally, both term frequency and TF-IDF, term frequency-inverse document frequency, weights be tested for performance improvement. Weighting by term frequency is the standard technique, however using TF-IDF weights incorporates the relative importance of a term to its observation and has been shown to improve performance [3]. For example, if a word has a high frequency but is common in all observations the TF-IDF will lessen its weight as this will be considered not as useful for classification purposes. Lastly, the usage of n-grams will be employed by treating the unit of text as a unigram (single word), bigram (consecutive words), and trigram (three consecutive words). This is an attempt to capture more contextual meaning by altering how the features are constructed. While this approach did not show improvement with sentiment analysis, it is possible it could improve code classification [4]. In these series of experiments, the performance of the NB classifiers is measured against the nCoder classified test set data.

### 2.3 Judging Classifier Output

Once the optimal NB classifier has been selected, the predicted values of the code will be compared against those predicted by nCoder. While it is interesting to note how often both agree on the presence and absence of the code, the area of primary concern is exploring the situations where two classification methods disagree. To test which technique is better, a sample of n=100 of both the false positive and false negative cases will be collected. A human judge will then blindly code each observation for agreement between one of the classification methods. Additionally, increasing the confidence threshold of the optimized NB classifier will be tested via human judgment. The default threshold in performing binary classification is 50%, however this may be increased to raise the likelihood of correct classification. This threshold will be increased and reexamined by a human judge to determine if the NB classifier can outperform nCoder.

## 3 Results

All resulting metrics use nCoder derived coding as the benchmark against which NB predictions are measured. Additionally, the metrics are measured with the code present as the positive case. The diagnostic metrics used to evaluate classification results are the accuracy, sensitivity, and specificity. The accuracy statistic reports the overall level of agreement between the NB and nCoder values. The sensitivity, or true positive rate, measures the correctly classified positive cases while the specificity, or true negative rate, measures the number of correctly classified negative cases. The metrics must be evaluated together when determining the optimal NB classifier as no individual value paints the whole picture.

**Table 11.** Naïve bayes classifier test results.

| Experimental setup | Laplace | Accuracy | Sensitivity | Specificity |
|---|---|---|---|---|
| Raw text | 0.5 | 0.927 | 0.662 | 0.967 |
| Post-processed unigrams | 0.5 | 0.937 | 0.779 | 0.964 |
| TF-IDF weighting | 0.5 | 0.860 | 0.869 | 0.801 |
| Post-processed bigrams | 0.5 | 0.845 | 0.335 | 0.967 |
| Post-processed trigrams | 0.5 | 0.773 | 0.080 | 0.990 |

The results listed in Table 1 report the diagnostic metrics for each of the experiments. Each experimental setup was tested over a range of Laplace smoothing parameters however only the best performance is reported for brevity; each family of experiments have similar results and are thus representative. These show the NB classifier using post processed text and term frequency weighting outperformed the other classifiers.

**Table 2.** Human adjudication of classification disagreement.

| | Overall | F. positive subset | F. negative subset |
|---|---|---|---|
| Human/naïve bayes agreement | 75 | 28 | 47 |
| Human/nCoder agreement | 125 | 72 | 53 |
| Total | 200 | 100 | 100 |

The results comparing nCoder and NB classification methods are reported in Table 2. Unsurprisingly, these results show nCoder outperforms NB based on the overall sample. However, an interesting pattern emerges when the results of the false positive and negative subsets are examined. Nearly all the difference comes from the subset of data where nCoder labels the code present while NB does not and warrants further examination where NB classification predicts the label and nCoder does not.

The confidence threshold of the NB classifier was raised from 50% to 90% confidence to determine if this will lead to outperforming nCoder. A sample of 200 observations was judged by a human rater from the test set where NB predicted the presence of the code and nCoder did not. These results showed NB outperformed nCoder by the human judge agreeing 59.5% of the time. This is statistically significant from equal performance of 50% ($t = 2.73$, p-value = 0.007) suggesting more is gained by using NB classification over nCoder in this scenario.

## 4 Discussion

These results suggest that incorporating machine learning into the qualitative coding process provides benefits over an approach only using nCoder. Using this methodology would increase the number of coded observations by 536 on top of the 14,449 identified by nCoder representing an increase of 3.7%. Further research can be conducted to determine potential impacts on using codes augmented with machine learning with modeling techniques such as Epistemic Network Analysis. This may allow for more efficient use of existing models in finding statistical patterns, and especially so for low base rate codes. Additionally, the NB classification approach is one of the simplest machine learning techniques and further research can explore how more sophisticated methods may improve the ability to re-code data in greater numbers. The main limitation with this study is the use of a code without thee-way validation. Using a fully validated code in addition to multiple human judges will increase the external validity of this approach and should also be considered for future study.

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# Communicating QE: A Two-Part Resource for Quantitative Ethnographers in Health Education and Health Care Contexts (Part 2 of 2)

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**Abstract.** Modeling human behavior, interactions and experiences while retaining direct links to the original qualitative data is a hallmark of quantitative ethnography (QE). A growing repertoire of QE approaches has guided researchers in multiple disciplines to quantify qualitative data in ways that are fair and actionable. In this two-part resource, we highlight how QE is being used to address research challenges in health education and health care contexts. This brief (part 2) discusses the application of QE in accounting for patient experiences and capturing interactions for quality improvement. Part 1 addresses how QE is being used to examine interventions intended to bridge health professions education and practice, mainly in the medical and nursing education contexts. For each research challenge, we also describe areas of opportunity. We argue that QE will facilitate new opportunities in educational assessment, participatory research, and health services and public health research.

**Keywords:** health care, patient-centered care, health services research, quality improvement, quantitative ethnography

## 1 Introduction

The body of quantitative ethnography (QE) research in the fields of health professions education and health care is expanding rapidly. Specific areas of application include, but are not limited to, patient-oriented research, healthcare quality improvement, implementation science, human factors/ergonomics and systems engineering in health care, and health policy analysis. Interest in conducting research in this area has emerged from a variety of disciplinary contexts (e.g., psychology, learning sciences, anthropology, human factors/ergonomics) and settings (e.g., higher education, health care systems, industry). But it can also be challenging to effectively communicate the processes, affordances, and constraints of conducting QE research with our collaborators, colleagues, and participants. We envision this brief as a resource that a) defines research challenges in health and healthcare contexts, b) argues for the advantages of applying QE research, c) points to worked examples, and d) outlines directions for future work. Our goal is not to compare QE methods to other research methods that are applied in this expansive field but rather to illustrate how QE methods and tools enable representational, analytical, and actionable ways of understanding phenomena in a range of health and health care contexts.

## 2 Accounting for Patient Experience

While there has been less QE research conducted to date on patient experiences than on other aspects of health and health care, this is an area of increasing attention by QE researchers. For example, Zörgő and colleagues [1] have studied how patients make therapeutic choices, Puetz [2] and Choi and colleagues [3] have examined the experiences of applicants for Social Security Disability Insurance, and Scheuer and Salihu [4] have explored patients' discussions of side-effects and withdrawal when prescribed antidepressants.

This body of work is growing in part because QE methods and techniques are particularly well suited to analyzing patient experiences at scale, either on their own or as part of broader models that incorporate health-care workers, institutions, or policy. For example, patient experience is often measured using survey instruments or interview protocols, which provide insight into, for example, the extent to which patients find clinicians to be open and respectful, whether they feel that their experiences and concerns are taken seriously, whether their expectations for the clinical encounter are met, and their understanding of and feelings about health and health care [5]. However, measures that rely on patient perceptions have a number of methodological limitations. Research shows that patients often overestimate the extent to which clinical encounters reflect patient-centered care, possibly due to response bias or simply because patients have not experienced a range of effective clinical practices [6]. Patient-reported data may even fail to account for important aspects of patient-centered care: for example, patients' reported satisfaction is generally influenced less by how much their health goals have been supported than by how they feel at the time of the survey; patients also tend to be less satisfied when their medical issues are complex and characterized by uncertainty [7].

Researchers often address these challenges by applying ethnographic methods to audio or video recordings of clinical encounters, but such studies are labor- and time-intensive and thus limited to analyses of small numbers of patients. Given the persistent and pernicious impacts of racism and other forms of both interpersonal and structural bias in health care [8], larger studies are needed both to facilitate fairness in the research itself and to account in depth for a broad range of patient experiences and clinical encounters.

QE methods address these challenges by enabling researchers to construct fair models of conversations between patients and clinicians (or among patients), patient testimonials or interviews, or other forms of natural language discourse at scale. Importantly, such models (a) can account for the unique contributions of clinicians, patients, and patient advocates in addition to modeling conversations or other encounters as a whole, and (b) when applied to records of clinical encounters, enable elements of patient-centered care, such as shared decision-making, to be measured directly rather than only indirectly through the perceptions or recollections of patients and clinicians. Moreover, such models could incorporate other sources of information, including patient surveys/interviews, outcomes, and other patient data, into a single measurement space, facilitating more dynamic and nuanced assessment of key clinical practices and patient experiences and outcomes.

## 3 Capturing Interactions for Quality Improvement

Health care is a complex sociotechnical system, with outcomes for patients, clinicians and other healthcare professionals depending on interactions within that system [9]. While human factors/ergonomics (HFE) researchers acknowledge the importance of understanding and anticipating interactions to improve quality and safety in health care, rigorous research methodologies to do so were sparse. QE helps to generate useful visualizations that quantify those interactions while facilitating linkages to the richness of our data. For example, Wooldridge and colleagues [10] used ENA to model interactions between clinicians in primary care teams to understand how role, hierarchy and technology influenced task allocation. HFE researchers have also used ENA to deepen theories related to interactions in systems, investigating how augmented reality technology influenced systems of learning [11] how characteristics of sociotechnical system designs shape healthcare team communication [12], and how system interactions influence work of caregivers of persons living with dementia [13].

While capturing those interactions is crucial to understanding complex systems, the next step is to (re)design those sociotechnical systems to improve outcomes for patients, caregivers and health care professionals. Thus far, QE, particularly through the use of ENA, has served to identify opportunities to address through redesign. An ongoing opportunity is to integrate QE methodologies in HFE-based, human-centered design processes, which tend to be participatory and constructive in nature [14-15] This integration could be mutually beneficial, with HFE approaches enriching the growing interest in participatory QE and QE approaches enabling the representation of complex datasets to participants in the design process. QE approaches to close the interpretive loop by involving participants in interpreting and using the data and models produced. These approaches will enhance participatory design practices. However, an ongoing opportunity for the QE community is to develop more interpretable models and practices to more easily and quickly orient participants, including patients, family/caregivers, clinicians and more, to QE models and data.

## 4 Concluding Remarks

Future directions in QE research on health and healthcare include not only continued engagement with the three research areas described in the two-part resource (bridging education and practice, accounting for patient experience, and capturing interactions for quality improvement) but also new ones. There is a considerable potential for the use of QE methods to analyze key interactions in public health programs, health policy ecosystems, and health care administration, as QE is well-suited to modeling multifaceted systems characterized by complex interactions. Such analyses could be transformative for research on, for example, the effects of large-scale interventions or policies on people and communities, which in turn could guide interventional design and policy development. While we cannot predict all the ways that QE might be used in health and health care contexts, it is clear from the early work of this research community that there are many rich opportunities to apply QE in ways that could improve health and healthcare for patients, practitioners, educators, trainees, and communities.

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# Edges in Epistemic Network Analysis

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**Abstract.** Epistemic network analysis (ENA) is a powerful tool for quantifying complex qualitative data. The visualization and analytical power of ENA could be extended by adding additional meaning to edges within networks including semantic relationships and the ability to connect more than two nodes. Here, we use Reddit data on social support for antidepressant side effects to highlight the ways in which ENA network edges could be extended with elements of semantic networks and hypergraphs. The types of support seen in discussions of antidepressant use on social media are representations of multiple complex conceptual relationships between potential side effects of antidepressants, cessation/withdrawal from antidepressants, and requests and offers for social support. Together, the elements of semantic networks, hypergraphs, and ENA provide a richer picture of complex interactions such as the discussions of antidepressant side effects in Reddit threads.

**Keywords:** Epistemic Network Analysis, Antidepressant, Side Effects

## 1 Introduction

Epistemic network analysis (ENA) is a unique visualization and analysis tool which can be used to synthesize qualitative and quantitative data to better understand relationships in a given culture [1]. A core component and strength of ENA is its ability to measure and represent relationships between concepts. In an ENA network, these relationships are depicted via network edges connecting two nodes, where nodes correspond to codes for concepts within the target culture. A connection is said to occur when codes co-occur within a pre-specified distance of each other. In a weighted ENA network, edge thickness, or weight, is proportional to the number of co-occurrences [1]. As with any approach, this method of edge creation relies on a series of assumptions. Here we examine these assumptions and identify potential directions for stretching the meaning of edges with an ENA network. To do so, we provide real-world examples using data from the social media site Reddit.

Antidepressant (AD) use or withdrawal can lead to side effects such as weight changes and sexual dysfunction which negatively affect patient quality of life [2-3]. These effects, as well as depression and the use of ADs themselves, are stigmatized topics. Reddit is a social media platform that encourages discussions of such stigmatized topics by providing the option of discursive anonymity and therefore increasing self-disclosure [4]. The study examines the relationship between AD side effects, withdrawal and types of social support present in threads on the subreddit r/depression. Social support in online discussions of health has previously been categorized using the Social Support Behavior Code (SSBC), which includes information, emotional, esteem, network, and tangible support types [5-7]. Loans and expressions of willingness to perform tasks on behalf of another are tangible assistance. Compliments, offers of validation, and attempts to relieve someone's guilt are esteem support. Network support includes offers to "be there" for another and access to companions or reminders of existing supportive individuals, while information support includes advice, providing factual information, reappraising situations, or giving referrals. Finally, emotional support can be divided into physical affection such as hugs, sympathy, empathy, encouragement, prayers, and reminders of the closeness of the relationship with the person being supported. Two additional support types, active listening and offers of confidentiality, are not applicable to a semi-anonymous online format. Improved understanding of the use of these support types in discussions of AD side effects on Reddit could inform future studies on discussions of AD use in healthcare settings.

The types of support seen in discussions of AD side effects on Reddit are representations of complex conceptual relationships between potential side effects, AD withdrawal, and requests and offers for social support. In an ENA network, the richness of description of these concepts and subsequent analysis is influenced by the level of specificity and nuance captured by network edges. ENA network edges could be improved with the addition of two features: 1. Freedom to note types of relationships between nodes (semantic relationships), and 2. The ability to connect more than two nodes (hypergraph elements).

## 2 Methods

In February 2021, threads containing the names of ADs were scraped from the subreddit r/depression using the Python API Wrapper [8]. Codes were developed inductively using the 10 longest threads with posts containing discussions of AD side effects. They were also developed deductively using a modified version of the SSBC. Threads were cleaned, segmented into sentences, coded, and aggregated with the R package and web-based interface associated with ROCK [9-10]. For illustrative purposes, figures and example excerpts included in this study were taken from the longest thread. For ENA, sentences were chosen as utterances to capture the multiple types of relationships between side effects and support types which often occurred within a given post or comment. A moving stanza window with a size of two was chosen based on manual inspection. Each post or comment was considered to be a unit of analysis, and one thread was a conversation. To accommodate the threaded nature of Reddit data, ENA networks were created with the recently developed threaded ENA using the R packages rENA and tma [11-13]. The semantic network diagram was created with qualitative network analysis (QNA) using the ROCK R package [9]. Hypergraphs were created manually.

## 3 Results and Discussion

### 3.1 Epistemic Network Analysis (ENA)

ENA network edges depict the number of times two codes co-occur within a stanza window [1]. Referring to the original data ("closing the interpretive loop") allows for interpretation of these co-occurrences. In the thread depicted below (Fig 1), dark, thick lines indicate that offers of personal experience co-occurred with discussions of dreams. This relationship typically occurred when a user shared their experience with the side effect of altered dreams, as in the following example: "I have weird lucid [dreams] on fluxotine..." References to dizziness also tended to occur with discussions of withdrawal and offers of empathy.

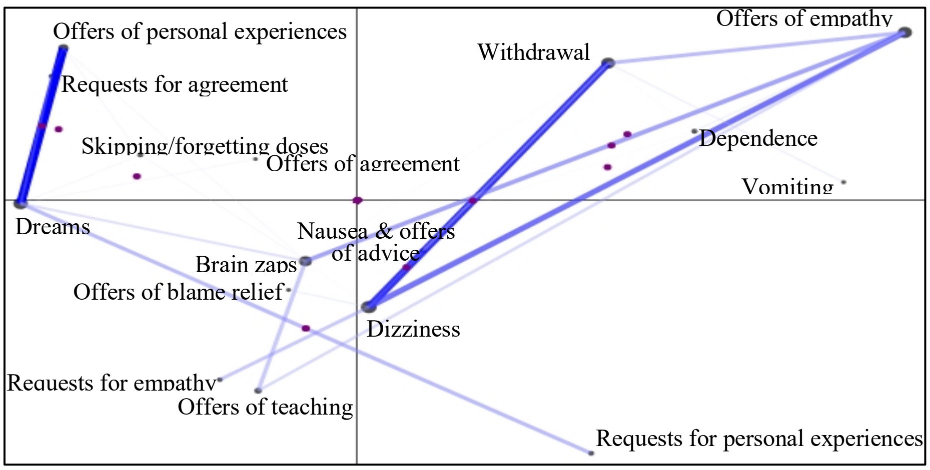


**Fig. 11.** Weighted epistemic network of social support types and AD side effects. Dizziness was discussed alongside withdrawal and offers of empathy. Reports of dream-related side effects and requests for personal experiences also co-occurred frequently.

### 3.2 Semantic Relationships and Hyperedges

Although ENA network edges depict co-occurrences of codes, they do not contain any information about the type of relationship between codes. There is much prior work on semantic networks and conceptual relationships. This work includes Con-ceptNet, a large semantic network and knowledge base [14], and the Unified Medical Language System semantic network, which identified 54 semantic links as part of a systematic effort to integrate multiple biomedical resources [15]. Previously identified connections include the "is a" relationship which describes attributes such as types, conceptual containment, and generalization [16]. For instance, dizziness is a side ef-fect of AD's. Additional relationships include causal ("produces", "result of"), tem-poral ("occurs with," "prerequisite event of"), spatial ("adjacent to", "surrounds"), and functional ("prevents," "motivation of") links, among many others [14-15].

Edges used in ENA networks connect only two nodes, but conceptual relationships often include three or more components. These relationships can be captured in hypergraphs, graphs in which more than two nodes can be connected by edges known as hyperedges. By linking more than two nodes, hyperedges allow for the ability to capture complexities of real-world systems that are difficult to represent in traditional graph structures [17].

To exemplify the utility of hyperedges, consider the following statement: "I went cold turkey and had the exact same situation. Vertigo to the point I was unable to leave the house for 3 days." This statement is an offer of empathy for dizziness caused by withdrawal. The connection of the three codes (empathy, dizziness, and withdrawal) is conceptually distinct from offering empathy for only dizziness only, as dizziness could be an AD side effect not associated with withdrawal. It is also different from offering empathy for withdrawal generally, as withdrawal often includes other additional side effects.

Expanding ENA edges to include semantic relationships between more than two nodes would increase the richness of data visualization and analysis within epistemic networks. For instance, the ENA network (See Fig. 1) contains three primary types of relationships: causality, support requests, and support offers. These relationship types and associated directionality can be captured with colored arrows using qualitative network analysis (QNA). For example, the three thickest edges in Fig. 1 are represented by black and blue arrows in Fig 2. A black arrow shows that withdrawal causes dizziness, while blue arrows indicate personal experience offers for dream-related side effects and empathy offers for dizziness. Green arrows depict requests for support, such as empathy requests for withdrawal.

The incorporation of semantic network properties and hyperedges in ENA raises issues related to network construction and interpretation. The present work is intended as a starting point for community discussion of edge meaning in ENA and the value of a multimethod approach to improve the depth and application of network analysis.

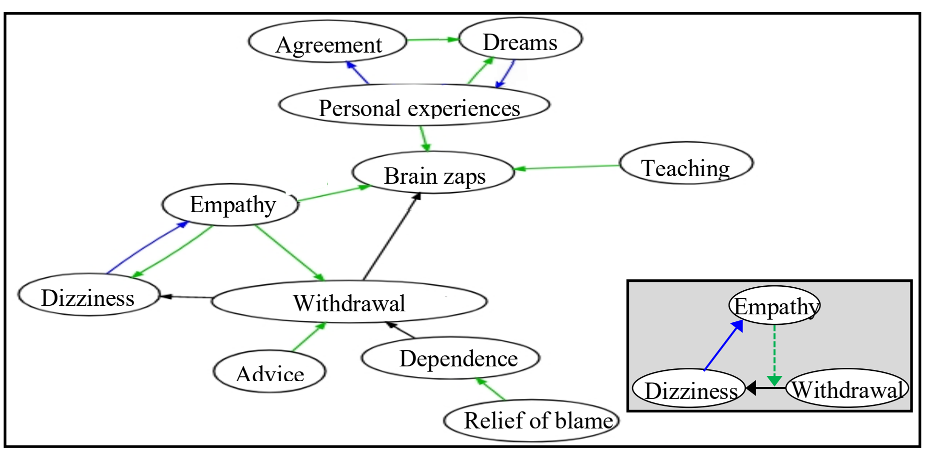

**Fig. 12.** Two qualitative network analysis (QNA) representations of support and AD side effects. Each node corresponds to a code. Arrows represent relationships between codes including causality (black), support requests (blue) and offers (green). Inset: Modified QNA representation showing a hyperedge connecting three codes. In addition to a causal relationship between withdrawal and dizziness (black) and requests for empathy related to dizziness (blue), the example thread included offers of empathy for dizziness caused by withdrawal (green dashed).

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# Understanding How Undergraduate Nursing Students (Learn to) Recognize Cues in Digital Clinical Experiences™: A Transmodal Analysis

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**Abstract.** Quantitative ethnography (QE) and epistemic network analysis (ENA) have provided fruitful methods for assessing the quality of nursing education. This study identified a phenomenon that previous QE-based analyses involving the use of simulations in nursing education have not explored and a traditional ENA approach would not have been able to model. Specifically, nursing students spent long periods of their learning in Shadow Health® Digital Clinical Experiences™ focusing deeply on one skill and not connecting to other skills and ideas. We found that not only did the learners focus specifically on a fundamental nursing skill of recognizing cues, but that within that one skill or code there were a variety of ways in which the learners where practicing the skill and the modality used in doing so. These results add motivation for the development of emergent QE approaches such as ordered ENA as well as multimodal and transmodal methods.

**Keywords:** Quantitative Ethnography, Nursing Education, Multimodal Analysis.

## 1 Introduction and Relevant Research

In the context of dynamic clinical settings, a key set of competencies new graduates need are conceptualized within NCSBN Clinical Judgment Measurement Model (NCJMM), a multilayer sociocognitive task model; and, Quality and Safety Education for Nurses (QSEN), a psychosocial and psychomotor competency framework. Exposure to clinical experiences is a hallmark approach for cultivating practice readiness; however, nursing programs also routinely integrate a variety of low- and high-fidelity virtual simulations within the curricula as a practical supplement. Consequently, it is important to understand how nursing students' professional praxis develops in and with support of these digital learning environments. We examined students' participation in Shadow Health® Digital Clinical Experiences™ (DCE) and focused on the foundational nursing skill of *recognizing cues*. This is an essential cognitive operation of NCJMM, and yet little is known about how the construct manifests among students' learning to practice this skill in virtual patient simulations (VPS).

In previous QE studies, researchers have visualized the interconnectedness of NCJMM and QSEN codes in dialogues exchanged between nursing educators, students, and virtual characters in the context of a Fundamentals of Nursing scenario [1]. Additional work in this area has demonstrated the use of QE to make sense of multimodal data streams and interpret collocated teamwork in healthcare simulations [2]. We build upon prior work in the field to examine one NCJMM construct using two forms of student data logged in DCE in the context of Health Assessment scenarios.

## 2 Shadow Health® Digital Clinical Experiences™ (DCE)

DCE is a suite of web-based, asynchronous, single-user VPS that allow undergraduate pre- and post-licensure nursing students to practice patient-centered communication, physical assessment, documentation, and clinical reasoning skills in a safe learning environment. In each simulation, the learner interacts with virtual patients formulating questions through typed or spoken speech and performs a series of physical examinations. Each virtual patient possesses a rich medical and sociocultural background that the learner can explore and address during the interaction. Throughout the patient exam, the learner can make empathetic statements upon the virtual patient's expression of an emotional, physical, or experiential difficulty. Likewise, the student can follow-up with educational statements after the virtual patient reveals a gap in their understanding of a relevant topic and could benefit from medical education. Each virtual patient can recognize and respond to thousands of questions and statements relative to the learning objectives covered in each scenario.

## 3 Participants, Data Sources, Coding, and Analysis

Two focused exam assignments from the undergraduate Health Assessment (HA) suite of simulations were purposefully chosen for this study: cough (respiratory) and abdominal pain (GI). In the respiratory assignment, the student (Lyssa, pseudonym) was provided with the opportunity to conduct a focused exam on Danny, an 8-year-old pediatric patient who is sent to the school nurse's office because he has been coughing. In the GI assignment, the student (Elton, pseudonym) conducted a focused exam on Esther, a 78-year-old patient admitted to the ER with abdominal pain. In both assignments students assumed the role of a healthcare provider, interviewed the patient about the history of their presenting illness and the functioning of other relevant systems, performed a physical exam to assess those related body systems, and completed post-exam activities (e.g., care plan activity). Transcripts were obtained from Fall semester of 2021 from two nursing students (#lines= 249 for Lyssa, #lines= 344 for Elton) enrolled in a BSN program at a university in the midwestern region of the United States.

Our initial approach to this analysis was to build from previous studies using Epistemic Network Analysis (ENA) to focus on patterns of connections between codes such as NCJMM and QSEN standards. However, during our iterative process of developing ENA models and using them to guide our close reading of the underlying qualitative data, we noticed an important phenomenon that is part of DCE's instructional design which ENA does not currently model. Specifically, learners were focusing on one skill for prolonged stretches of their learning and not connecting it to other skills, but rather seemed to be focusing on refining the performance of that one skill in isolation. Thus, for each student, each textual utterance and exam action was coded for the occurrence (1) or absence (0) of recognizing cues. Recognizing cues was defined as the practice of identifying relevant information about a patient from different sources (e.g., medical history, vital signs). To understand how each student was practicing this skill, we identified overall patterns in their process and nuances in their choices. We also identified how the system scaffolded their emergent skill.

## 4 Findings, Discussion, Conclusion, and Implications

Lyssa's transcript had a total of 213 instances (or lines) of recognizing cues. Over 43 instances, Lyssa gathered subjective information about 8-year-old Danny's history of present illness (HPI) to fully understand the patient's symptoms. In addition, the student gathered information about Danny's past medical history (PMH) to identify any risk factors and engaged in a review of systems (ROS) to understand associated symptoms. Lyssa also briefly attempted to understand measures Danny took for infection prevention. This was followed by 170 exam actions, where Lyssa was seen obtaining objective information through inspection of vital signs (e.g., blood pressure, pulse oximetry, respiratory rate, heart rate) and body parts (eyes to back).

Elton's transcript had a total of 311 instances (or lines) of recognizing cues. 213 instances of interactions could be characterized as cue recognition because of Elton's questions and Esther's responses about HPI, ROS, and PMH. In addition, Elton performed a neurological assessment to gauge the patient's alertness and obtained information about 78-year-old Esther's activities of daily living (ADL), instrumental activities of daily living. (IADL), and social history (SH) before proceeding to her physical exam. Elton performed 88 exam actions for inspecting Esther's vital signs and body parts (heart to abdomen). Lyssa and Elton's transcripts revealed that they both exclusively recognized cues or gathered patient information during the assessment phase. Both students also first engaged in textual utterances followed by exam actions. These findings are not surprising and rather expected in undergraduate students who may not be as proficient as expert nurses yet to simultaneously blend interactions with physical examinations. Lyssa's heavier reliance on exam actions and why Elton chose to interact with the patient a lot more may be justified given that the former was assessing a pediatric patient and latter was assessing a female geriatric patient. Finally, as students gathered subjective information, the DCE system translated some textual utterances to questions that mimicked expert nurses' questioning. The system also supported objective information gathering by providing immediate feedback on students' exam actions and prompting a response from the patient. Table 1 illustrates a snapshot from each student's interaction with their respective virtual patients, and feedback from the DCE system.

Our qualitative analysis revealed the role of textual utterances and exam actions in helping nursing students recognize cues in the context of Health Assessment scenarios involving a pediatric and a geriatric patient. We also demonstrated the role of DCE in enabling students to practice various components of health assessment (e.g., HPI, ROS, SH, ADL, PMH) and model good questioning to obtain a complete picture of their patients. Taking multiple modalities into account will be important for QE approaches to examine the depths and breadths of constructs within complex phenomena. The work of additional researchers is pushing the field in a similar methodological direction [2]. Subsequent work in this project will focus on expanding our ability to understand nursing students' learning processes in DCE. We will incorporate additional student transcripts, details such as EHR documentation, and quantify qualitative data to better understand students' cue recognition and their application of subsequent cognitive operations in NCJMM (e.g., analyzing cues). Emerging innovations in QE such as ordered network analysis (ONA) [3] may be explored to model directional connections between a collection of codes or constructs and itself. Such an approach could account for prolonged focus on one skill/code/construct. Doing so could also allow us to project a network of possible moves nursing students make while engaging in DCE as it relates to the NCJMM. This study contributes to the growing body of literature on how digital alternatives to physical clinical experiences can contribute to the development of nursing students' practice readiness.

**Table 12.** Cue recognition examples.

| Feature | Student | Example |
|---|---|---|
| Interaction | Lyssa | Patient: My breathing seems good. My nose is kind of runny right now, but I can still breathe ok.<br>Lyssa: Do you have any pain when breathing?<br>Patient: No, I don't think anything is wrong with my breathing. |
| | Elton | Elton: How long have you had stomach pain?<br>Patient: The pain started as a general discomfort, about five days ago, when I started having the… difficulties going to the bathroom.<br>Elton: Has the pain changed? |
| Exam action | Lyssa | [Lyssa palpated frontal sinuses]<br>DCE: No tenderness reported<br>[Lyssa palpated maxillary sinuses]<br>DCE: No tenderness reported |
| | Elton | [Elton palpated lower left quadrant with light pressure]<br>DCE: Tenderness reported; palpable guarding and distention; no masses<br>Patient: Mmm, it feels sore there. |
| System scaffolding | Lyssa | Lyssa: Have you been exposed to germs?<br>[DCE clarified to "Have you been around anyone sick?"] |

| | |
|---|---|
| Elton | Elton: What is your pain at the highest?<br>[DCE clarified to “Can you rate your current pain level on a scale of 0 to 10?”] |

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# Communicating QE: A Two-Part Resource for Quantitative Ethnographers in Health Education and Health Care Contexts (Part 1 of 2)

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**Abstract.** Modeling human behavior, interactions and experiences while retaining direct links to the original qualitative data is a hallmark of quantitative ethnography (QE). A growing repertoire of QE approaches have guided researchers in multiple disciplines to quantify qualitative data in ways that are fair and actionable. In this two-part resource, we highlight how QE is being used to advance research in health education and health care contexts. This brief (part 1) addresses how QE is being used to examine interventions intended to bridge health professions education and practice, mainly in the medical and nursing education contexts. Part 2 discusses the application of QE in accounting for patient experiences and capturing interactions for quality improvement. For each research challenge, we also describe areas of opportunity. We argue that QE will facilitate new advancements in educational assessments, participatory research, and health services and public health research.

**Keywords:** Medical Education, Nursing Education, Health Professions, Quantitative Ethnography

## 1 Introduction

The body of quantitative ethnography (QE) research in the fields of health professions education and health care is rapidly expanding. Specific areas of application include, but are not limited to, patient-oriented research, healthcare quality improvement, implementation science, human factors/ergonomics and systems engineering in health care, and health policy analysis. Interest in conducting research in this area has emerged from a variety of disciplinary contexts (e.g., psychology, learning sciences, anthropology, human factors/ergonomics) and settings (e.g., higher education, health care systems, industry). However, it can be challenging to effectively communicate the processes, affordances, and constraints of conducting QE research with our collaborators, colleagues, and participants. We envision this brief as a resource that (a) defines research challenges in health professions education and healthcare contexts, (b) argues for the advantages of applying QE research, (c) points to worked examples, and (d) outlines directions for future work. Our goal is not to compare QE methods to other research methods that are applied in this expansive field but rather to illustrate how QE methods and tools enable representational, analytical, and actionable ways of understanding phenomena in a range of health professions education and healthcare contexts.

## 2 Bridging Education and Practice

A goal of medical and nursing education programs is to support students' practice readiness. This necessitates understanding how the design and implementation of curricular innovations contribute to students' development of knowledge, skills, and attitudes that are beneficial for their participation in complex clinical settings. QE offers a novel set of methods and tools to examine the efficacy of learning environments for facilitating professional praxis. Recent examples discuss ways that QE methods may be used to better understand both processes and outcomes of health profession educational paradigms. For instance, traditional Epistemic Network Analysis (ENA) was used to model and trace shifts in pre-licensure nursing students' discourse with peers, faculty, and characters in virtual reality (VR) simulations [1]. This QE work was central in demonstrating visual and statistical evidence about how undergraduate nursing students, even in first year and second years, can learn to practice a web of interpersonal (e.g., patient centered care, teamwork, and collaboration), psychomotor (e.g., performing patient assessments) and cognitive skills (e.g., recognizing and analyzing cues). Furthermore, QE was well-suited for understanding how faculty orchestrate pre-briefing, VR simulations, and debriefing to meet clinical education goals. In another paper, Shah and colleagues [2] illuminated how nursing faculty skillfully use their technological, pedagogical and content knowledge to help students make connections between theory and practice about patient assessment, safety, and care. Thick descriptions about nursing students' actions, reflections, and learning trajectories provided additional evidence about the effectiveness of faculty-moderated VR simulations [3].

An additional goal in health professions education is to support the development of skills in team-based and individual clinical problem solving and performance. QE methods have been used to investigate team collaboration in the emergency medicine setting as well as clinical reasoning, error detection, and application of clinical skills in surgery. For example, Sullivan and colleagues [4] used ENA to distinguish among high and low performing trauma resuscitation teams, finding that higher performing teams offered up information in an unprompted fashion while lower performing teams spent more time requesting information and behaviors from team members. Additionally, Ruis and colleagues [5] found that ENA helped to shed light on how novices versus relative experts utilized a minimally invasive hernia repair simulator. Novices tended to use the simulator to learn specific technical skills while experts utilized the simulator primarily to explore thought processes and clinical reasoning. Further, studies in surgery have also utilized ENA to look at the importance of error detection and management related to operative skills and outcomes. Surgical residents who better recognize errors and think strategically about error management have better outcomes in simulated hernia repair [6].

Multiple forms of data on health care activity and health education processes can now be logged in physical and digital environments. The application of emerging QE approaches is (a) helping facilitate discoveries about how members of a healthcare team function (in training and in practice) and (b) revealing patterns about how students practice professional skills. For instance, Buckingham Shum and colleagues [7] demonstrated one way to make sense of multimodal data streams and interpret collocated teamwork in healthcare simulations. Shah and colleagues [8] used transcripts from undergraduate nursing students' participation in digital clinical experiences to understand the nature of one construct (i.e., cue recognition). They examined textual utterances (e.g., questions, responses, prompts) and exam actions, and found developmental similarities and contextual differences in how students gathered relevant patient information.

Many specialties and training programs within the health professions are moving toward competency-based models of education and assessment, which can help to link program practices and trainee performance to patient outcomes. One approach to investigate the development of competence requires the frequent collection of workplace-based assessments based on clinical practice. "Micro-assessments" capturing frequent snapshots of actual clinical performance combined with written or verbal feedback can be modeled using QE approaches to look at progressions in clinical practice and autonomy. Additionally, Asch and colleagues [9] found that obstetrical residency programs could be ranked by maternal complication rates experienced by graduates' patients. However, medical licensure examination scores did not reflect these differences. QE techniques can help us learn from low-and high-performing programs in a holistic manner and allow us to influence evidence-based policy changes [10].

Finally, an emerging innovation that may be particularly useful in health education and care contexts is Ordered Network Analysis (ONA). This technique allows for examination and statistical comparison of the order and direction of elements in collaborative environments [11]. ONA may also catalyze new measurement opportunities so we can understand nuances in the movement of single codes or constructs within the larger network of connections. We may also assess patterns in how novices master specific skills (e.g., clinical judgment) or improve specific skills (e.g., medical administration errors) over time.

## 3 Concluding Remarks

Future directions in QE research on health professions and health care include not only continued engagement with the research areas described in the two-part resource (bridging education and practice, accounting for patient experience, and capturing interactions for quality improvement) but also new ones. QE is well suited to provide researchers with tools and approaches to examine how cultural shifts in the health professions and methodological innovations in education practices are aligning for learners (in training and in practice) in individual settings and at scale. Just as important as understanding an intervention or environment is involving participants in the use of the data and models that are produced from any research. Collaborative research involving diverse stakeholders from academia, hospitals, home and the community, and industry is burgeoning. The use of participatory approaches in QE examinations could foster inclusion of additional participant voices, including educators and students, healthcare professionals, patients, caregivers, product developers and user-experience researchers in joint sensemaking. It would also strengthen the claims we make about the efficacy of health professions education interventions and health care experiences [12]. While we cannot predict all the ways that QE might be used, it is clear from the early work of this research community that there are many rich opportunities to apply QE to improve processes and outcomes for patients, practitioners, trainees, and communities.

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# Examining Effects of Organizational Context on the Implementation of Clinical Innovations: A QE Approach

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**Abstract.** This study examines the discourse of healthcare practitioners who participated in the implementation of an evidence-based intervention at either a community or academic health center. A quantitative ethnographic (QE) approach will be used to model the discourse of study participants and explore their perceptions of how Organizational Contextual Factors (OCF's) influence the fidelity of the intervention.

**Keywords:** Antimicrobial-Stewardship, Fidelity, Implementation Science.

## 1 Introduction

Classic studies indicate that it takes 17–20 years to get clinical innovations, including evidenced-based interventions (EBIs) into practice; moreover, fewer than 50% of clinical innovations ever make it into general usage [1]. It is widely acknowledged that adaptation to the local context may have both positive and negative impacts on implementation [1-2]. An Epistemic Network Analysis (ENA) technique can be useful in modeling the structure of connections in the data, the contextual factors, and implementation outcomes. Specifically, ENA analyzes all the networks simultaneously, resulting in a set of networks that can be compared both visually and statistically [3].

## 2 Theory and Research Questions

The Consolidated Framework for Implementation Research (CFIR) provides descriptors to understand the characteristics of change, as well as a framework for supporting the management of a variety of "organizational contextual factors" (OCF) during the change process. This framework can also be used to guide formative evaluations and build an implementation knowledge base of OCFs across multiple studies and settings. CFIR is composed of five major domains: inner setting, outer setting, intervention characteristics, the process of implementation, and characteristics of the intervention [2]. Another concept – Fidelity – has been used as a measure of the degree to which an EBI was implemented as was intended. Research into the spread and adoption of EBIs is therefore concerned with the impact that OCFs have on intervention fidelity [4]. The following research questions were examined in this study: (1) What are the OCFs that influence the implementation of an EBI at two different healthcare settings (i.e., Community vs. Academic) and (2) do these OCF's influence the fidelity of EBI differently at these sites? The implications of this study are described later in the paper.

## 3 Methods

### 3.1 Procedure

Data was extracted from a larger study evaluating a multi-site implementation of a fluoroquinolone pre-prescription authorization intervention. Semi-structured interviews were conducted with a total of 18 participants (e.g., Medical Doctors (MD) = 8, Nurse (N) = 1, Pharmacist (P) = 7, Site Coordinators (SC) = 2) at 4 different hospitals (e.g., 3 AHC, 1 CHC). Study participants were actively involved in the design and implementation of the EBI in their respective hospitals. Discourse during semi-structured interviews was between moderators and healthcare providers.

### 3.2 Data Coding and Analysis

Transcripts were audio-recorded and transcribed so that each line designated a new turn of talk. Lines within the interviews were coded based on the CFIR Framework: (1) specific implementation constructs and (2) whether the excerpt was about a barrier to or a facilitator of implementation. Individual respondents were the unit of analysis, and each utterance was coded for the occurrence (1) or nonoccurrence (0). The ENA model includes the codes below:

**Table 13.**

| Code(s) | Definition(s) | Example(s) |
|---|---|---|
| Inner setting | Characteristics of the implementing organization (team culture, compatibility, etc.). | "…the single hardest bump we had to get over was, was discussing with researchers how this is research…" |
| Outer setting | External influences on intervention implementation (i.e., external policies, resources, etc.). | "During COVID, so we kind of shifted to a 50/50 on site work from home." |
| Intervention characteristics | Aspects of the intervention that may impact implementation success. | "Since the Fluroquinalone (FQ) Best Practice Alert (BPA) only fires in a very specific set of circumstances… I didn't find it intrusive or as annoying." |
| Implementation process | Stages of implementation such as planning, execution, and evaluation. | "…we had someone that was clinical information that kind of could provide insight into building the order set." |

| | | |
|---|---|---|
| Fidelity | Quality in which the Fluroquinolone (FQ) intervention is followed/completed by the organization. | "You know, as I kind of mentioned, the alert is kind of in line and built the way that all the other alerts in our house system." |
| Facilitators | Factors that enable the organization's ability to implement the intervention. | "I think from a usability standpoint, it's pretty, it's easy to use." |
| Barriers | Factors that obstruct the organization's ability to implement the intervention. | "The research committee process here is so dysfunctional." |

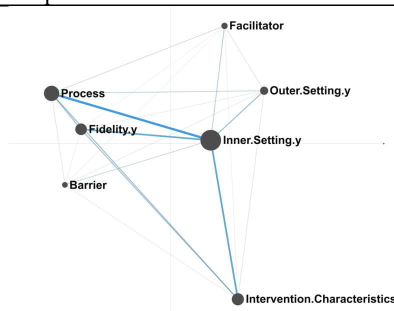
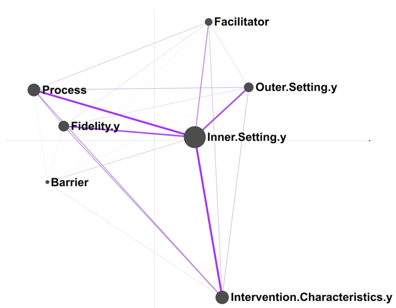
### 3.3 Epistemic Network Analysis

Epistemic Network Analysis was applied to analyze the data that were defined as the units of analysis as all lines of data associated with a single value of Site Type (e.g., AHC's and CHC). The ENA algorithm uses a moving window to construct a network defined as 7 lines within a given conversation.

## 4 Results

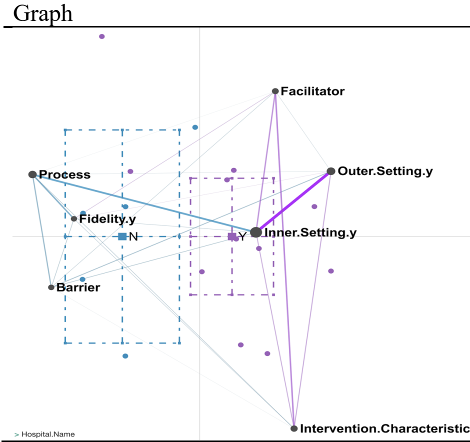
Using a QE Approach, this study highlights (1) the OCFs that influence the implementation of an EBI at two different healthcare settings (i.e., Community vs. Academic) and (2) the OCF's influence on the fidelity of EBI at these sites. After reviewing the qualitative data, it was discovered that there were significant differences in how stakeholders discussed their implementation process during post-implementation interviews. The CHC discussions revolved around the implementation strategy, inner setting, and fidelity. Meanwhile, AHC's stakeholders highlighted more connections between the outer setting, inner setting, and fidelity. An interesting finding is that CHC stakeholders perceived that there were more barriers associated with their implementation process when referring to these OCF's however the AHC's stakeholders perceived that there were more structures in place to facilitate their implementation process. CHC discourse focused more on connections between process and inner setting meanwhile, AHC's focused more on the inner setting and outer setting. The faint and thin line connecting fidelity indicates that on average both organizations made the same number of connections between these topics (See Table 1).

**Table 14.** Qualitative results.

| Org type | Graph | Example |
|---|---|---|
| Community health center |  | Ex: I created a document with different screen shots of the BPA alert just really (Inner Setting) outlining to them, you know, how to work through and follow that (Process) in terms of, again, bringing the patient up for ASP review and then looking at how do you resolve that alert that has fired (Fidelity) and designating, you know, if ID approved it or not and which provider followed up on that.<br>Ex: Barrier – "The research committee process here is so dysfunctional." |
| Academic health center |  | Ex: We're just a 250-bed hospital (Inner Setting) here, and I think we've already done a…before this study kind of came about… (Outer Setting), just with all the side effects that come along with fluoroquinolones we over the past couple of years, we've just been doing a lot of education about alternatives anyways (Fidelity).<br>Ex: Facilitator - "I think from a usability standpoint, it's pretty, it's easy to use." |

The table below represents both types of organizations, despite having commonalities in connection patterns between the OCF's, The ENA model highlights the differences mentioned above between the two organizations (See Table 2).

**Table 2.** Quantitative results.

| Graph | Results |
|---|---|
|  | Along the X axis, a two sample t test assuming unequal variance showed N (mean=-0.92, SD=0.54, N=5 was statistically significantly different at the alpha=0.05 level from Y (mean=0.38, SD=0.77, N=12; t (10.79)= -3.93, p=0.00, Cohen's d=1.81). |

## 5 Discussion

This study highlights how OCF's may influence the implementation of EBI's and provides some insights into how implementation strategies should be tailored to facilitate successful adoption to different organizational contexts. Rather than simply focusing on how best to spread an intervention, leaders should consider if the intervention is a good fit for the context, will the intervention work as intended, and assess what may be some unintended consequences associated with the introduction of an intervention.

**Acknowledgements.** This project was in part supported by grant number R01HS026226 from the Agency for Healthcare Research and Quality and by grant number UL1TR002373 from the Clinical and Translational Science Award (CTSA) program, through the NIH National Center for Advancing Translational Sciences (NCATS).

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# Epistemic Network Analysis on Asian American College Access Literature

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**Abstract.** Conducting a literature review is a key part of understanding how a field is addressing a certain topic. To better conceptualize the breadth of a chosen field, I use Epistemic Network Analysis (ENA), to identify gaps in the literature about Asian American college access. Using R, I identified keywords from abstracts, pulled from three different databases using the search phrases "Asian American College Access". Keywords were identified using a deductive coding approach based on the research question, "What are the gaps in Asian American college access literature". Based on the epistemic network, I found that there is not frequent overlap between the term "Asian American" and "Access", and "Education". Additionally, there is less distinction between the term Asian American and more specific ethnic/racial groups such as "Southeast Asian", and "South Asian". Additionally, this study applies ENA to a new set of data to explore what topics are connected and discussed in literature on Asian American college access and offers new techniques to understanding research discourse within a field of study.

**Keywords:** Epistemic Network Analysis, Asian American, East Asian, Southeast Asian, South Asian, College Access.

## 1 Introduction

Conducting a literature review is a critical part of understanding the conversations happening in a field of study. For novice researchers especially, but also for academics exploring a new research topic, literature reviews can often be overwhelming because they contain a wealth of information from past framing to pivotal findings. The struggle to systematically explore and document key topics and patterns in existing literature has also been well-documented [1-2]. Assessing and understanding the breadth and depth of literature is particularly essential in research on marginalized groups; for example, Poon and colleagues [3] conducted a systematic literature review of Asian Americans and Pacific Islanders, to argue there is more to Asian Americans than the model minority myth. To address the challenge of identifying broad themes across the literature, I posit that ENA can be an important tool for literature reviews. For this study, I use Epistemic Network Analysis to identify the gaps in Asian American college access literature to address the research question, “What are the gaps in Asian American college access?”

## 2 Conceptual Framework

Asian Americans have often been cited in education literature as highly successful and stereotyped as the model minority [3-6]. The model minority myth is the assumption that, broadly, Asian Americans are successful and high achieving particular in STEM fields. Although data may point to this being true in some cases, this is broadly not generalizable across all Asian American populations. Teranishi [7], found that there are differences across Asian American groups when comparing first year academic success, particularly differences between East Asians and Southeast Asians. Nadal [8] also argues for distinctions between Asian American groups because of the different immigration contexts that brought Asian Americans to the United States.

Research has found differences in disaggregating data; for example, Southeast Asian American (SEAA) students often rely on their social capital to access higher education [9]. In contrast to East Asian students who are often expected to attend college [10]. These two studies included similarities such as parents being unable to provide resources; however, there are a wide range of differences in Asian American experiences. Because these distinctions exist, Asian American scholars have called for data to be disaggregated.

## 3 Methodology

To begin compiling my comprehensive literature review, I began by manually downloading and documenting each article. Data variables include inclusion in the review (articles that adhere to inclusion criteria or do not), publication year, title, and the segmented text. This set includes abstracts or the first paragraph of the article, and it is assumed that the content in these sections will be most likely to synthesize the key points of the comprehensive work.

To prepare the data for coding, I first used R to segment the data and identify key words which I selected deductively. The codes can broadly be organized into two different categories, terms around the racial categorization of Asian Americans and terms that describe college access. The codes about the racial categorization include Asian, Asian American, Pan-Asian, Pan-Ethnic, East Asian, Southeast Asian, and South Asian. The regional groups of East, Southeast, and South Asian were developed from existing research from Nadal [8], who argues for a more nuanced understanding of Asian American categorization which is consistent with past literature in the field of higher education towards data disaggregation [11]. The second category of codes refers specifically to issues of college access which can span from the application process to environmental factors.

## 4 Results and Discussion

Figure 1 shows the epistemic network for the articles that were included in my literature review. The model shows the relationships between the themes through the distance of nodes, the size of the nodes, and the thickness of the nodes. Additionally, this network includes each of the articles and how related they are to each topic. The network shows that there is a strong relationship between Asian American and Asian, and that terms such as Asian American, Asian, and Pan Ethnic, are often not used associated with the separate terms "college" and "access". Proximally, education is very distant from the terms Asian, Asian American and Pan Ethnic. The thickness of the lines shows that despite the proximal distance, that there is still some relationship between the points. For example, Kim and Zhao [12] argue that Asian American labor-market performance exceeds that of women, while controlling for education as a variable. In this case education is used as a variable to be controlled rather than college access. Another example is Nadal [8], who mentions education, but the articles main focus is not education. The relationship between Asian and Asian American indicates that despite referencing different populations, the two seem to be used interchangeably [3]. For example, Hsia and Hirano-Nakanishi [13], write about the rise in Asian Americans in higher education; however, they also address immigration of Asians from Asia. Additionally, the network shows, that studies that I selected typically cluster around Access, and Southeast Asians, and outside education. This indicates that there is literature address ing Southeast Asian and access.

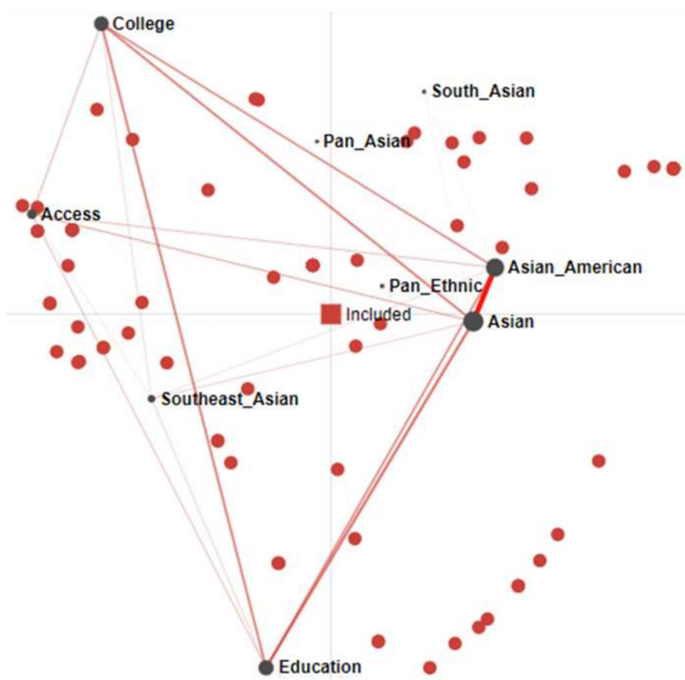


**Fig. 13.** Epistemic network of themes. Each unit mean is an article in the literature review.

## 5 Conclusion

Through this brief study, I identified themes in the literature and areas that require more research while showing new ways to engage with research on Asian Americans. This study has shown the potential utility of quantitative ethnographic techniques such as ENA for visualizing patterns literature-based discourse and demonstrates the first applied steps in how ENA can be used to visualize the relationships between key themes in extant literature. Future research will explore how to set authors as units rather than titles of articles to show the relationship that authors have to different themes.

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# Using Ordered Network Analysis to Visualize Ideologies in Political Survey Data

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**Abstract.** This study tested a novel empirical method to analyze individuals' political ideologies using online survey data. Instead of inferring latent variables from responses to standard opinion questions or from bodies of text, this study explicitly asked survey respondents which of their opinions provided reasons for their other opinions and used the responses to generate Ordered Network Analysis diagrams of the resulting relationships among ideas. Despite the small sample size, we conclude that individuals responded in plausible and meaningful ways. The methodology presented in this study can inform future research with larger and more representative samples.

**Keywords:** Ideologies, Ordered Network Analysis, Survey.

## 1 Introduction

Researchers often survey individuals about political issues and ideas and seek patterns in the data. For example, they use factor analysis to seek latent variables to explain the phenomenon of public opinions and behaviors. However, individuals' political views have complex structures in which the relationships among the ideas are important [1]. Using factor analysis and related methods is not suited to revealing such complexity and variety [2].

In this study, we analyzed peoples' political ideologies using a novel empirical method: in an online survey, we asked people which of their opinions provide reasons for their other opinions and used the responses to generate network diagrams of the resulting relationships among ideas. The specific network method we used to visualize the survey data is Ordered Network Analysis (ONA) [3], which can represent the co-occurrence of concepts by accounting for the order of events in directed networks.

## 2 Background

Previous studies had explored understanding individuals' political thoughts as complex structures of ideas and visualizing them as networks or structures of connected ideas.

Examples include narrative-networks, morphological analysis, and cognitive-affective mapping [4]. For example, Homer-Dixon and colleagues construe "ideologies as complex systems", and argue that "At the individual level, the elements [of these systems] are ideas, beliefs, and values, whose interactions give rise to a person's understanding of society, which in turn guides individual political behavior" [5]. These studies usually derive models of complex political idea-structures from qualitative interpretation of extensive bodies of text or from correlations in the survey responses of large samples, which cannot identify individual networks [6]. In this study, we use the visual affordances of ONA to represent the structure of ideas as networks. ONA models the co-occurrence of concepts and visualizes the directional relationships between concepts in directed networks.

# 3 Methods

## 3.1 Data Collection

We conducted an online survey through Amazon Mechanical Turk (AMT). We recruited 93 respondents who have US residency, liberal political opinions, and an age of 18 or higher.

Respondents were shown a list of 30 possible issues as shown in Figure 1 and asked, "Which of these would you like to see happen? For each pair of issues they selected, they were asked, "Are you in favor of [A] because you are in favor of [B]"? The respondents chose between 3 and 18 issues (mean = 7.4) and identified between 0 and 100 connections (mean = 26.8). No two respondents gave identical responses. The respondents were also asked to rank five prominent Democratic politicians "in order from the one who most often says things you agree with (at the top) to the one who least often says what you agree with (at the bottom)." In descending order of popularity in this sample, the politicians were: Bernie Sanders, Barack Obama, Alexandria Ocasio-Cortez, Elizabeth Warren, and Joe Biden.

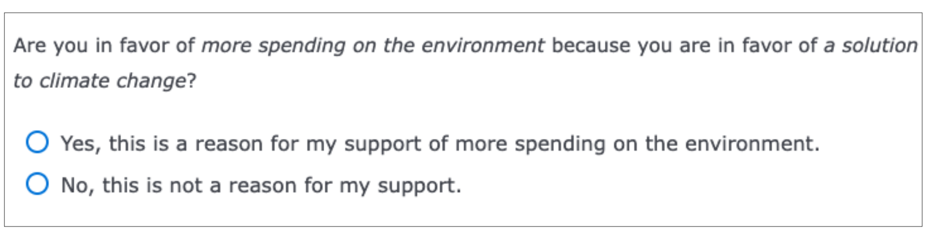


**Fig. 14.** An example of survey items respondents answered in the online survey.

## 3.2 Data Analysis

To conduct ONA, we first labeled each pair of connections respondents made using the 30 issues, which were represented as nodes in ONA network visualizations. For each pair of connection, they are connected using a triangle-shape edge with a chevron indicating direction on it, as shown in Figure 2. For example, in the context of this study, we interpret A as a *reason* and B as an *outcome* in response to the reason. In ONA, node size represents the relative frequency of a node being an action. The larger the node is, the more often it is being an action in the network.


**Fig. 2.** Edges between each pair of codes in ONA represent a directional relationship. In the context of this study, we interpret A as *reason*, B as *action* in response to the reason.

## 4 Results

We describe two examples that have moderate numbers of nodes and edges, because they lend themselves best to narrative summaries (See Fig. 3).

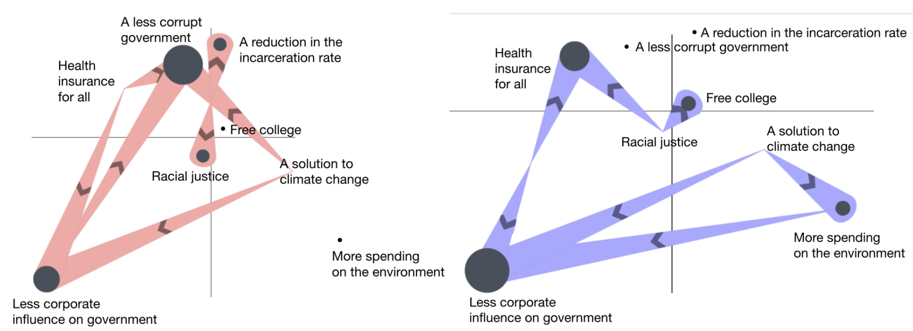


**Fig. 3.** Left side: The ONA network of a 37-year-old white man who ranks Sanders first and Obama last among the Democratic politicians and places himself at 2 on a 1-10 ideological scale (where 0 is the furthest left). Right side: The ONA network of a 38-year-old Asian American man who also ranks Sanders first and Obama last and places himself at a 1 on the ideology scale.

In Figure 3 left, A LESS CORRUPT GOVERNMENT is the code that has the largest node size, meaning that in this network it more often acts as an outcome. This respondent sees addressing CLIMATE CHANGE, providing HEALTH INSURANCE FOR ALL, and LESS CORPORATE INFLUENCE ON GOVERNMENT as reasons to reduce government corruption, as indicated by the three chevrons pointing from the aforementioned three codes to A LESS CORRUPT GOVERNMENT. Additionally, he connects REDUCING THE INCARCERATION RATE to RACIAL JUSTICE, pointing the arrow in both directions. This respondent, although, does not make any connection with code MORE SPENDING ON THE ENVIRONMENT.

In Figure 4, the code that has the largest node size is LESS CORPORATE INFLUENCE ON GOVERNMENT. Specifically, this respondent sees addressing CLIMATE CHANGE, SPENDING MONEY ON THE ENVIRONMENT, and HEALTH INSURANCE FOR ALL as reasons to reduce corporate influence on government, as indicated by the chevrons pointing from the aforementioned three codes to LESS CORPORATE INFLUENCE ON GOVERNMENT. Additionally, this respondent also sees a bidirectional relationship between HEALTH INSURANCE FOR ALL and LESS CORPORATE INFLUENCE ON GOVERNMENT, meaning that he thinks providing universal health insurance can not only be seen as a reason to reduce corporate influence on government, but also as responsive action. This respondent also sees RACIAL JUSTICE as a reason to make COLLEGE FREE and to provide UNIVERSAL HEALTH CARE. He sees SOLVING CLIMATE CHANGE as a reason for ENVIRONMENTAL SPENDING.

The differences between the two networks above can also be visualized using a difference graph as shown in Figure 4. All the units in the same ONA model share a set of fixed node positions, and such affordances allow the creation of difference graph by subtracting the line weights of each connection in one network from the corresponding connections in another network.

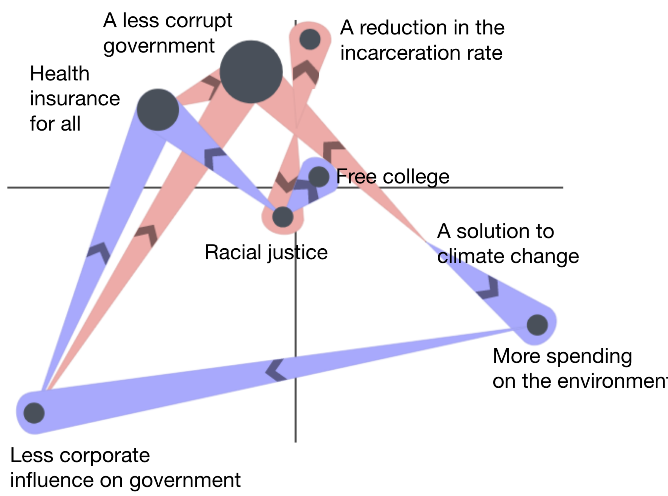


**Fig. 4.** The difference graph of the network in Figure 2 left (red) and Figure 2 right (purple).

As Figure 4 shows, LESS CORPORATE INFLUENCE ON GOVERNMENT features importantly in both networks, as it leads to two nodes that have the largest node size in each network: HEALTH INSURANCE FOR ALL and A LESS CORRUPT GOVERNMENT. Similarly, A SOLUTION TO CLIMATE CHANGE leads to A LESS CORRUPT GOVERNMENT in the red network, while leads to MORE SPENDING ON THE ENVIRONMENT in the purple network.

## 5 Discussion

In this study, we analyzed 93 individuals' political ideologies using ONA and we found that individuals often gave meaningful, interpretable, and reasonable responses when making connections. For instance, the reasons that were most often asserted all make sense on their face; the reasons that were most commonly rejected do not look plausible.

Substantive social outcomes often provided reasons for process reforms, but not the reverse, which again seems reasonable. Although with a small sample size, we conclude that findings from this study have practical implications to inform future research with larger and more representative samples.

**Acknowledgements.** This work was funded in part by the National Science Foundation (DRL-1661036, DRL-1713110), the Wisconsin Alumni Research Foundation, and the Office of the Vice Chancellor for Research and Graduate Education at the University of Wisconsin-Madison. The opinions, findings, and conclusions do not reflect the views of the funding agencies, cooperating institutions, or other individuals.

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# Reflections on How Japanese and US Media Reported the 2022 Beijing Winter Olympics Opening Ceremony

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**Abstract.** Studies of media and news indicate that social ideology and news types will affect news topics and content perspectives. As a world-renowned sports event, the 2022 Winter Olympics was held in the shade of the COVID-19 pandemic yet still attracted the world's attention. This paper examines how Japanese and US news media reported the 2022 Beijing Winter Olympics differently. Short forms of news reports and long forms of news analyses were collected and analyzed using the Epistemic Network Analysis (ENA) method. Findings show diverse patterns in different news forms in different languages on the same topic reporting the 2022 Winter Olympics opening ceremony. While Japanese media tended to focus more on the opening ceremony and related Olympics history, the US media were more likely to pin on the hosting country's related issues like contentious human rights arguments and political boycotts. These observations echo the existing findings that news topics and content are affected by social ideology and news types.

**Keywords:** Quantitative Ethnography, Epistemic Network Analysis, Reflections, Winter Olympics, News Report.

## 1 Introduction

The Winter Olympic Games is a world-renowned sports event, and hosting world-class sports events during the pandemic can boost people's confidence in fighting the pandemic. Thus, it is not surprising that the 2022 Beijing Winter Olympics attracted the media's attention worldwide. The opening ceremony, which can best highlight the national images and cultural characteristics, was reported by the media from various countries spending a large quantity of resources and energy [1].

Reading through related news from the Japanese and United States (US) media, the content and tones in the two languages show different patterns. According to Li [2], how mainstream media of the two countries reported the topics and content perspectives of the Winter Olympics opening ceremony is mainly due to their cultural factors, public opinions, government attitudes, habitual reporting methods, and other factors. Moreover, different news types will also affect the news topics and content formatting.

## 2 Methods

The data analyzed in this reflection consists of news posts and analyses that reported the 2022 Beijing Winter Olympics. After filtering the news, there were 103 news articles written in Japanese and English in total, and each news was seen as an utterance and categorized as either a report or an analysis. To verify the correlation of the news with the Opening Ceremony topic, each researcher proofreads every news to ensure either its title or content contains the keyword: Opening Ceremony.

Sharing the same codebook written in English, two groups of raters coded and finished the social moderation process in Japanese and English news separately. Epistemic network analysis (ENA) webtool was used to model the connections between constructs used in this dataset [3]. Researchers applied a minimum edge weight of 0.05 in the network model to enhance the visibility for presenting the most salient connections in the visualization process.

**Table 15.** Codebook of constructs used in the analysis.

| Construct | Definition |
|---|---|
| Boycott | Official diplomatic boycotts against China holding the Winter Olympics. |
| China-Russia relation | Bilateral international relations between China and Russia. |
| Russia-Ukraine relation | Bilateral international relations between Russia and Ukraine. |
| Other countries | Other international affairs such as South Korea, New Zealand, etc. |
| Human right | China's domestic affairs, including Xinjiang, Uyghur Muslims, etc. |
| Pandemic control | Methods used by the Chinese government to control the pandemic during the Winter Olympics, including quarantine, testing, vaccine. |
| Economy and technology | The funds and technology China invested in the Winter Olympics. |
| Olympic history | Referring to mentioning any past Summer and Winter Olympics. |
| Opening ceremony | The introduction about the opening ceremony itself, such as parade, fireworks, countdowns, etc. |

## 3 Results

ENA was applied to compare the different patterns and connections in Japanese and US media reporting the 2022 Beijing Winter Olympics. The nodes represent each coded construct, and the edges that connect the nodes represent how strong the connection between each construct is. Since each news is a complete utterance and isolated from other news, the conversation was set as a whole conversation rather than moving stanza windows. Thicker lines represent stronger connections, and thinner lines, in contrast, represent weaker connections. For all the models, the edges were scaled to 1.5, and the minimum edge weights were adjusted to 0.05 for visualization optimization.

Figure 1 shows the overall ENA network models for the nine constructs in Japanese and US news. The x-axis is defined by the Opening Ceremony on the left side and the

Russia-Ukraine Relation on the right side. The y-axis is defined by Pandemic Control on the top and Boycott at the bottom. The strongest connection from Japanese news is between the Opening Ceremony and Olympic History, followed by Opening Ceremony and Pandemic Control. The most robust connection from the US news is between the Human Right and the Boycott, followed by Opening Ceremony and Olympic History, and Opening Ceremony and Pandemic Control.

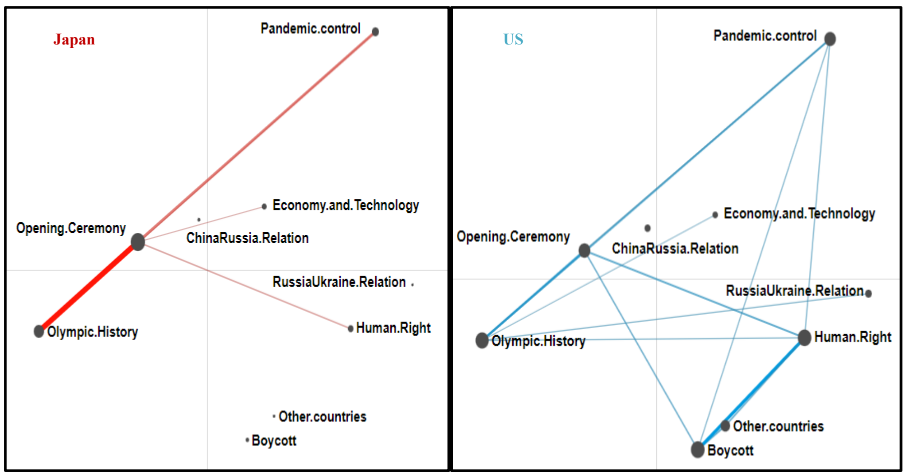


**Fig. 15.** ENA network models of media discourse patterns for Japan (left) and the US (right).

## 4 Discussion

This study examined how Japanese and US media reported the 2022 Beijing Winter Olympics in different patterns. ENA models are applied to check the overall discourse patterns between Japanese news and US news. In general, the weight of the Japanese connection is stronger than the US side, which indicates certain topics appeared in pairs more often in the Japanese news than in the US news. The connection between the Opening Ceremony and Olympic History is the strongest in the Japanese news, followed by Opening Ceremony and Pandemic Control. While from the US sources, the most robust connection is between Boycott and Human Right, followed by Opening Ceremony and Pandemic Control.

### 4.1 Limitations and Future Directions

This paper analyzes and compares the differences in news topics and content perspectives between Japanese and US mainstream media in their coverage of the 2022 Beijing Winter Olympics opening ceremony, demonstrating that different news formats in the Japanese and US media present different modes of expression for the same topic. However, the current study has at least two notable limitations. First, this study does not indicate how opening ceremony audiences respond to the topic-related news. Media coverage can transmit values through news and discourse, thereby subliminally influencing audiences' perceptions and judgments.

The second limitation of this study lies in overlooking the connections between social media networks and traditional news websites. With the rapid development of the Internet and social media expanding, audiences are no longer mere recipients of information. As they receive information from different outlets, audiences can feed their opinions on social media platforms in real-time, thus influencing the news topics' choice and opinion expression in media, forming an interactive structure between media and audiences. Many reactions and comment threads about the 2022 BeijingWinter Olympics opening ceremony on diverse social media platforms are worth further in-depth research.

In conclusion, this study applied Epistemic Network Analysis models to complete a preliminary reflection on how Japanese and US media reported the 2022 Beijing Winter Olympics opening ceremony differently. In general, it can help us better understand the different news types in media coverage, as well as the cultural and socio-ideology influences on news reporting.

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# Doctoral Consortium

# The Reshape T1D Study: Using the Strengths of Participatory Ethnography in Patient and Clinician Led Research to Understand the Type 1 Diabetes Lived Experience

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**Abstract.** Type 1 diabetes (T1D) is a chronic condition that requires constant daily management including insulin therapy and regular access to healthcare services. Our research seeks to answer two main questions: (1) what is T1D healthcare experience like in Alberta? and (2) how can T1D lived experiences in Alberta reshape care to suit the needs of people living with T1D?
Objective: To understand the opportunities and challenges in providing T1D care, identify factors associated with reduced quality of care, and provide recommendations for T1D health care.
Methods: We used narrative-based inquiry to understand the T1D lived experience. Participants must have attended specialty care within 3 years and be at least 18 years old. Recruitment occurred through *www.connecT1D.com*, *www.ReshapeT1D.com*, and social media. Data was generated using a patient and clinician co-designed pre-questionnaire and semi-structured interview guide. Each interview was transcribed verbatim, and codes were developed inductively using Interpretive Phenomenological Analysis by four raters using the Reproducible Open Coding Kit (ROCK). A tentative code structure was carefully crafted through repeated triangulation before final code tree development. We will use Epistemic Network Analysis (ENA) to model networks of code co-occurrences in discourse data.
Preliminary Findings: Common themes in stories include a greater need for flexibility in access to healthcare, more robust mental health resources in the clinic, and financial insecurities around healthcare coverage.

**Keywords:** Type I Diabetes, Mixed-Methods, Quantitative Ethnography.

## 1 Goals of Research

To demonstrate the power of partner-oriented research in T1D and understand the T1D lived experiences in Alberta using quantitative ethnography (QE).

## 2 Background

Type 1 diabetes (T1D) occurs when the pancreas is unable to produce adequate insulin, leading to exogenous insulin dependency, and a greater risk for complications [1]. People living with T1D face a constant burden of daily management that often leads to burnout and distress.

## 3 Methodology

Using a narrative-based inquiry approach we have interviewed n=41 people living with T1D in Alberta through non-proportional quota sampling based on the following strata: sex (male/female), geographic region (urban/rural), education (high school/college/university/professional). Participants must have been an Alberta resident of >18 years of age and living with T1D and accessing care for 3+ years. Participants were recruited through the online research recruitment platform *www.ConnecT1D.*ca, our own study website *www.ReshapeT1D.*com, and through Twitter and Facebook Alberta T1D communities. We collected data through a patient and clinician co-created pre-questionnaire and semi-structured interview. The pre-questionnaire included collection on demographics include sex, age, gender, ethnicity, urban vs rural, education, employment status, and health insurance status, as well as diabetes related questions.

The semi-structured interview focused on themes through Interpretive Phenomenological Analysis about appointments, barriers, adaptability and resilience, and accessibility and will be transcribed verbatim and coded in two phases. Coding began with four raters (1 patient partner, 2 clinicians, and 1 epidemiologist) freely coding 5 unique sets of transcripts, followed by iterative discussion of codes in triangulation, and the development of a final code tree. Coding and segmentation will be performed with the Reproducible Open Coding Kit (ROCK) [2]. As part of ongoing participatory QE, patient and clinician raters will be asked to conceptualize and draw their own ENA models based on their coding experience, results pending. Following coding, we will use Epistemic Network Analysis (ENA) [3] to model code co-occurrences in discourse data and explore sample-level characteristics to address our research questions.

## 4 Preliminary Findings and Contributions

Initial findings identify a need for greater flexibility in timing and scheduling of appointments. Patients identified a need for mental health professionals in the diabetes clinics as well as the financial insecurities of healthcare coverage. This research will demonstrate the importance of participatory QE, patient and clinician partnered research, and insights into in how people access T1D healthcare in Alberta.

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# Understanding Early-Career Mathematics Teaching Identities and Instructional Vision

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**Abstract.** Many elementary teachers enter the profession with anxieties about teaching mathematics. Though teacher education programs often strive to alleviate these anxieties, the process of learning to teach math is complex, and novice teachers enter the field with little support for continued learning. The proposed study seeks to understand how early-career teachers negotiate their own identities and instructional vision in different organizational contexts and with different supports. Using multi-modal data collected from teachers in their first three years of teaching at different schools and with different backgrounds, the study will employ Epistemic Network Analysis along with comparative qualitative case studies to understand the complex dimensions of early-career teachers' experiences.

**Keywords:** Epistemic Network Analysis, Mathematics Teaching Identity, Early Career Teachers, Professional Learning.

## 1 Goals of Research and Project Background

The goal of this proposed dissertation study is to gain understanding of how early-career teachers–those in their first three years of teaching–negotiate their own mathematics teaching identities and instructional visions in different school environments and with different supports. Although specific definitions of math identity vary, most studies adopt a Meadian concept of identity [1], viewing identity as multiple, evolving, and socially constructed–simply put, it is the story we tell ourselves about our relationship to mathematics in different contexts based on our experiences [2]. Research suggests elementary teachers' mathematics identities influence their instructional practices [3-4] and studies have begun to explore the importance of identity work in pre-service education and in-service professional development [5-6] to help support positive mathematics teaching identities and foster high-quality instructional vision. However, when early-career teachers enter classrooms in schools with different normative perspectives on how math should be taught, it can be difficult for them to continue to develop and maintain their positive mathematics teaching identities and instructional vision [7]. The proposed three-paper dissertation was developed through the work of multiple pilot projects examining mathematics teaching identity, instructional vision, and the use of online inquiry groups to support early-career teachers' continued learning. As such, the research takes a dynamic systems approach to identity [8] to consider the different internal and external factors that influence how early-career teachers negotiate their mathematics teaching identity and instructional vision. The study seeks to explore three research questions:

1. How do school environments influence early-career teachers' mathematics teaching identities and instructional vision? (Paper 1)
2. What supports do early-career teachers describe as influencing their mathematics teaching identity and instructional vision? (Paper 2)
3. How do early-career teachers' mathematics teaching identities and instructional visions change throughout their first year(s) of teaching? (Paper 3)

## 2 Methodology

The proposed study will use epistemic network analysis in three distinct ways. The sample for each paper will vary slightly: participants will be drawn primarily from two teacher education programs. Data for analysis will include interviews conducted at the beginning, middle, and end of the 2022-2023 academic school year. Paper 1 will use ENA to compare the connections between novices' identities and instructional visions through the coding of lesson plans and interview responses. Paper 2 will use ENA to compare reflective journal prompts and interviews to understand the influence of two interventions of support for novice teachers to understand shifts in mathematics teaching identity and instructional vision. Finally, Paper 3 will use ENA to model how teachers' mathematics identity and instructional vision change over time, using Dear Math letters, a reflective letter each novice writes about their experiences learning mathematics at the beginning and end of participants' teacher education program. Qualitative case studies will be employed to close the interpretive loop for each paper.

## 3 Preliminary or Expected Findings

Based on prior pilot studies and existing research on mathematics teaching identity, instructional vision, and the influence of school environments, I anticipate that the shifts in participants' mathematics teaching identity and instructional vision will differ based on their school environment and their opportunities for professional learning and support. Specifically, those participants in the intervention groups might be able to better maintain and continue to expand their identity and instructional vision.

## 4 Expected Contributions

Gaining a deeper understanding of the experiences of early-career teachers could help teacher education programs and local schools to better design systems that help to support positive mathematics teaching identities and high-quality instructional vision as novices enter the classroom. Further, the proposed study will contribute to research on mathematics teaching identity by helping to understand the different internal and external factors that influence how early-career teachers negotiate their personal identities in different normative environments.

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# Theoretical Foundations for Pattern-Making Logic from Limited Data Using Causal Models in Machine Learning

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**Abstract.** Current machine learning systems have severe theoretical limits due to (1) mathematical limitations preventing the extraction of patterns from limited data (2) limiting generalizability, and (3) insufficient large and reliable data sets required for machine learning (ML) and deeper causal modeling. Might there be a way to overcome these limitations by focusing on the appropriateness of generalizing small data sets isolated from their causal context? Quantitative ethnography (QE) encourages narrowing the field of inquiry to specific contexts of cultural interpretation, which typically produce smaller data sets. When coupled with techniques of Epistemic Network Analysis (ENA), meaning can be derived from smaller data sets in the context of larger ones, modeling their structure and network of connections and interconnections within the situation—including causal relationships and possible future states. A holistic framework of causation is conceptualized for the development of pattern-making logic using data elicited from previous use cases containing declarative knowledge of direct digital harm experiences containing rich descriptions and cultural material for edge-in modeling. These models serve as the basis for cross-cultural machine readable inputs enabling rich contextual mental model simulation for applications in cross-domain Situational Awareness (SA) models.

**Keywords:** First Keyword, Second Keyword, Third Keyword Qualitative Ethnography (QE), Epistemic Network Analysis (ENA), Situational Awareness (SA), Pattern-Making Logic, Limited Data, Causal Model, Machine Learning (ML), Continuous Adaptive Learning (CAL), ML-Human Learning, AI Ethics, Digital Harm, Algorithmic Harm, Adaptive Ethnographic Network Technique, Artificial Intelligence (AI), Sustainability.

## 1 Goals of the Research

The goals of this research are to: (1) facilitate the advancement of ML-human integrated learning theory and practices; (2) to enable continuous adaptive machine learning (ML) in simultaneity with human-decision making; (3) by exploring how ML might accelerate mutual cognition, adaptive-thinking, and SA decision-making; (4) through ML mental model processing and simulation; (5) to reduce instances of overconfidence and bias; (6) that reinforce and accelerate existential risk from algorithmic harms; (7) enabling more resilient and adaptive networks, leadership and governance required for a sustainable ML and artificial intelligence (AI) future.

## 2 Background of the Project

Anticipated and unforeseen observable patterns of transformation are reinventing key nodes of our global ecosystem, governance, and society [1]. Troubling evidence sup ports the premise that the "invisible hand" has been hijacked by God-like machines who own command and control of our attention—capturing our minds, directing our thoughts and future behavior—for private interest, profit, and power [2]. Industry 4.0 [3] is offloading indeterminant risk to society. Prediction and control of natural and social processes have been summoned through the Meta-gate [4], into an invisible parallel, leaving hubris institutions fragmented and operationally irrelevant [1]. Our state has surpassed human sensemaking capacity [5]. Algorithmic harms amplify historical trauma and structural violence at unprecedented speed and scale—no longer discriminant to person or country, affecting the human condition at scale. Will the quantum turn lead to the discovery of sustainable AI [6] or Extinction 6.0 [7]?

## 3 Methodology

This paper proposes a research design that balances well-established ML-human integrated learning theory with ENA [13] practices to fit techniques of network ethnography to models of ML [8-10, 12]. A Situational Analysis (SA) causal model provides the holistic framework for the creation of mental models where rich data about its structure, network, and state can be combined with larger data sets to tease out inferences about causes and consequences, creating previously unattainable data, transformed with meaning—enabling pattern-making logic required for ML. To test this hypothesis, mental models are created from data elicited from previous use cases containing declarative knowledge of direct algorithmic harm experiences containing rich descriptions and cultural material. Data is identified through a systematic literature search performed via keyword queries on 51 repositories to identify literature for analysis containing one or more of the following key terms: "digital harm," "algorithmic harm," "artificial intelligence danger," or "automated decision making," and "cultur*," and "digital ethnography," between 2020 and 2022. The search identified 120 unique artifacts for review, including "What about us? Preserving LGBTIQ+ history of forced displacement," "Family secrets: Exploring unexpected paternity through direct-to-consumer DNA ancestry tests," "The limits of labelling: Incidental sex work among gay, bisexual, and queer young men on social media," and "Digital media and domestic violence in Australia: Essential contexts." Ethnographic techniques capture additional inputs related to the physical and virtual spaces of analysis [14]. Embedded ML processes enable a feedback loop in simultaneity [1, 15] between the machine and human during the model simulation and SA decision-making. Network ethnography is used for parallel supervised (subjective, ML) and unsupervised (objective, classical ML) processes that converge during data interpretation using a "snap back" reflexive check to look for overconfidence and bias [7]. Naturalistic categorization provides a protocol for quantifying SA effects on ML training [8].

## 4 Preliminary or Expected Findings

Each SA casual model simulation may provide a basis for a "simulation-turn" reflection and comparison of the various group and organizational units within a network ethnographic analysis, including their positionality to one another [9-11]. Adaptive network techniques open a range of approaches to determine the most effective method—which may not turn out to be just one or the other.

## 5 Expected Contributions

Advancing ML-human learning theory and practices into the realm of deep learning (DL) by demonstrating the use of ENA to operationalize SA causal models to elicit pattern-making logic during simultaneous ML-human learning. ML-human SA oriented simulations might allow for counter-causal remediation to support algorithmic transparency and harm mitigation—or "algorithms for good." ML-assisted decision-making reduces failure rates over time due to the speed and scale of model simulation of evermore complex mental models as they can combine to inform greater situational complexities. The iterative between adaptive interaction (reflexive, learning) and positionality leads to different, more sustainable outcomes since the justification of cooperation are factfinding and visualizing a path forward. When comparing simulations between networks of power, trust increases when joint knowledge building is separated from active powering—this is true in the political, social, and security contexts—and provides simulated outcomes for consideration in algorithmic and artificial intelligence (AI) related policy crafting.

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# Reponses to Support in Discussions of Antidepressant Side Effects on Reddit

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**Abstract.** Discussions of antidepressant (AD) side effects are hindered due to stigmatization of AD use and common side effects including sexual dysfunction. Because social media promotes disinhibition and self-disclosure, sites such as Reddit are well-positioned to provide information on these stigmatized topics. This pilot study investigates responses to social support in discussions of AD side effects on the subreddit r/depression. It provides an example of the utility of ENA for threaded data and contributes to work on communication about AD side effects which may inform patient support.

**Keywords:** Antidepressant, Side Effect, Epistemic Network Analysis

## 1 Background, Goals and Methodology

Antidepressant (AD) side effects significantly impact patient quality of life and medication adherence [1-2]. However, the associated stigma can impair discussions of AD side effects. Because social media promotes disinhibition and self-disclosure [3], sites such as Reddit offer a unique opportunity to study these stigmatized topics. Previous studies using data from the subreddit r/depression suggest social support varies based on AD class, and posts and top-level (L1) comments tend to refer to different types of side effects [4-5]. Building on this prior work, this study focuses on responses to support in discussions of AD side effects on r/depression. It characterizes responses present in these discussions and uses epistemic network analysis (ENA) to identify which responses accompany different types of support [6-7]. Deeper understanding of the responses provoked by various types of support may inform future studies of discussions of antidepressant use in healthcare settings.

Reddit threads with antidepressant names were scraped from r/depression using the Reddit API PRAW in February 2021 [8]. For this pilot study, data was restricted to posts, L1 comments, and their immediate replies (L2 comments) from the 20 longest threads with posts discussing AD side effects. Threads were coded using the online interface and R package associated with ROCK [9-10]. Codes were developed deductively, based on the Social Support Behavior Code [11], and inductively. Threaded ENA was used to generate epistemic networks with the rENA and tma R packages [7, 12-13].

## 2 Preliminary Findings and Expected Contributions

Discussion of side effects and support occurred across posts, L1, and L2 comments. A small group of distinct response categories were also present in comments. Responses were generally positive, with gratitude occurring the most frequently, followed by reports of feeling encouraged or experiencing happiness on behalf of another user ("second-hand joy"). A few users also said that they were taking advice they had been given, and one said the discussion caused them to change their mind.

Gratitude tended to follow descriptions of redditors' personal experiences (See Fig. 1). For example, posts asking for others' experiences with side effects elicited L1 comments on those experiences, and responses included thanks. Gratitude also followed or occurred within comments offering encouragement (See Fig. 1), for example "Thank you for sharing this and offering up a positive experience. Sending good vibes to you." Support offers were not restricted to comments. In one post, the original poster (OP) offered their experience of side effects with the intent to provide support ("…this has been my honest account of my personal experience…I hope someone finds this useful"). L1 comments echoed OP's experience and described feeling encouraged to read OP's side effects lessened over time (See Fig. 1), for example, "…the lack of quality sleep has kind of skewed my sense of reality. Knowing that by sticking to the medication will improve the side effects over time is definitely something I needed to read."

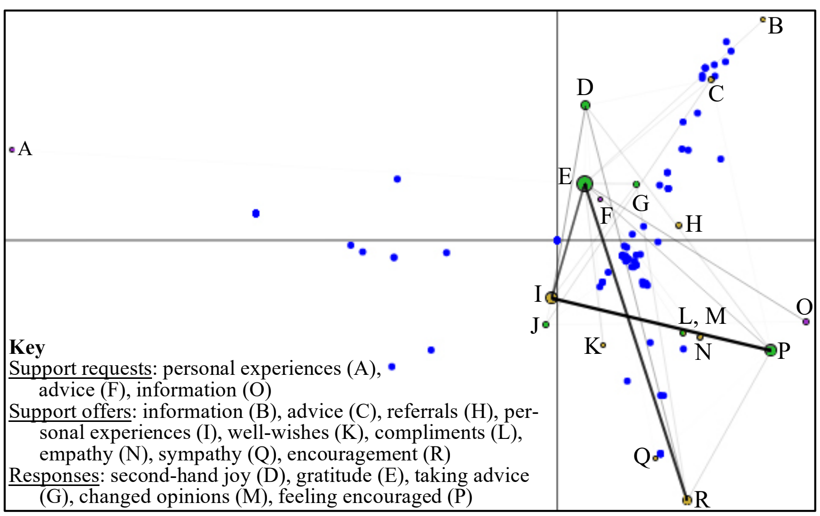


**Fig. 16.** Weighted epistemic network of support requests (purple), offers (orange), and responses (green). Edges not including a response type were included in network creation but are not shown to emphasize relationships with responses. Points correspond to posts and comments.

This study extends prior work on social support in AD side effect discussions on Reddit by emphasizing responses to differing types of support and expanding analysis beyond immediate responses to posts. Future work will compare responses based on types of ADs and side effect discussed. Improved understanding of responses to support may inform the way in which healthcare providers support patients during discussions of AD use. More broadly, this study showcases the applicability of the recently-developed version of ENA suitable for threaded data [7].

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# Geographic Analysis of Asian American College Access

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**Abstract.** Asian Americans consist of a panoply of differing ethnic national origins but are often characterized as a monolithic identity in education research. This shared racial identity, while powerful in some ways, can minimize important differences between ethnic groups by consolidating Asian American statistics and experiences. To address this, I analyze census tracts in Philadelphia where South Asians, Southeast Asians, East Asians, and Filipinos are highly clustered using Local Indices of Spatial Autocorrelation (LISA). I use college access indicators such as median income, frequency of college attainment, and racial indicators to explore how Asian Americans ethnic groups have different neighborhood environments based on ethnic background related to their geographic boundaries, which shape how they access local education resources contributing to post-secondary attainment.

**Keywords:** Geographic Information Systems, Asian American, College Access.

## 1 Goals of the Research

Asian Americans comprise a panoply of distinct intersectional identities, histories, and experiences, yet Asian Americans are essentialized as a group and broadly stereotyped as the model minority. Within Asian American populations there are differences across ethnic groups such as information to college access and campus resources [1–3]. Teranishi and colleagues [4] found that Chinese and Korean Americans had the greatest representation in selective institutions; however, within ethnic groups, there exist differences in socioeconomic status. Because of such cases, scholars and researchers have called for the disaggregation of Asian American data to ensure that ethnic minorities are supported within the Asian American racial category [1]. Although existing literature has shown differences across ethnic groups and socio-economic status, I expand upon this literature by including a geographic component: utilizing geographic information systems (GIS) to map the socioeconomic, education, and racial indicators in areas that are highly clustered and high frequency across Philadelphia County.

## 2 Methodology

I use data from the 2019 American Community Survey (ACS), primarily relying on data that describes highest level of education attainment, Asian country of origin, and annual income. These variables were selected using Perna's [5] conceptual model of higher education focusing on the school and community context. To place this in a geographic context, I mapped the spatial correlation between these variables.

### 2.1 Spatial Autocorrelation: Local Indices of Spatial Autocorrelation (LISA)

LISA is defined as having two properties: (1) the LISA for each observation gives an indication of the extent of significant spatial clustering of similar values around that observation and (2) the sum of LISAs for all observations is proportional to a global indicator of spatial association. In our case, each census block is calculated individually and then summed to provide the I from Moran's I. The calculated LISA describes each block's effects on the clustering within the data.

After these census tracts were identified, I removed any census tracts where two or more Asian American populations both clustered and overlapped in high frequencies. This allowed me to identify census tracts that were unique to ethnic enclaves to understand how enclave conditions differed from others. After this, I ran a nonparametric Kruskal-Wallis test to determine whether the mean ranks of the groups are different. Next, to determine which groups were significantly different I used a pairwise Wilcox test to identify which ethnic groups differed by educational attainment, region of origin, and household income.

## 3 Findings and Future Research

This study found that when Asian American groups are aggregated into smaller ethnic/racial categories, significant clustering exists across Philadelphia. Additionally, based on these clusters there were significant differences across income, education attainment, and proximity to other racial groups. Specifically Southeast Asians, comprised of Vietnamese, Cambodian, Lao and Hmong Americans, were in closer proximity to Black communities, while East Asians and South Asians were in closer proximity to White populations. Dache [6] found that Black, Latina/o and low-income student in Rochester typically did not have the same access to higher education as White higher income residents. Asian ethnic groups straddle similar lines yet are still racially categorized as Asian American. These findings support past studies that have found differences between among Asian American populations but innovates by providing spatial nuances that can be used to better understand and improve educational outcomes for diverse Asian American learners.

This study found spatial patterns across Philadelphia County and where Asian Americans are situated. However, this research does not address experiences of families in these geographic spaces. The next steps of this research is to provide qualitative con text, through interviews with participants from a local Philadelphia organization that focuses on Southeast Asian youth. I hope to utilize participatory epistemic network analysis (ENA) to collaboratively identify and understand themes from their experiences, which should inform the geographic relationships that currently exist in Philadelphia.

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# Unraveling Temporally Entangled Multimodal Interactions in CSCL Environments

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**Abstract.** This proposal aims to unravel temporally entangled multimodal interactions in computer-supported collaborative learning (CSCL) contexts to capture the essence of the collaborative meaning-making process with the help of MMLA and QE approaches. We will investigate primary modes being used during learning processes in an online CSCL environment and systematically model these multimodal interactions as a comprehensive model that accounts for the complex interplay among the multimodal events, considering temporal sequencing. This study will contribute to extending theoretical and methodological underpinnings for understanding complex interactions during learning processes in CSCL contexts.

**Keywords:** Multimodal Learning Analytics, CSCL, Temporality.

## 1 Goals and Background

In CSCL environments, learning occurs through *multimodal interactions*, which comprise both verbal and nonverbal interactions such as gestures, tool use, and so forth. These multimodal interactions often contemporaneously occur in specific sequences that dynamically contribute to the collaborative meaning-making process. For instance, one person's click event to view a learning resource may be in response to a verbal comment and impact others' subsequent speech and co-speech gesture behaviors. In order to grasp the core of how collaborative learning evolves in such instances, it is critical to model the dynamic interplay between different modes with consideration of its temporal structure [1]. We propose novel analytic methodologies employing MMLA [2] and discourse analysis techniques based on QE approaches [3]. Our goal is to unravel temporally entangled multimodal interactions in CSCL to capture the essence of the collaborative meaning-making process.

## 2 Methodology

In the spring semester of 2022, we recruited K-12 math pre-service teachers (N=33) from universities in the United States and provided an augmented embodied geometry curriculum that enables teachers to perform mathematically relevant body movements and collaboratively design new body-based actions to promote students' embodied mathematical thinking. Before and after the intervention, we conducted semi-structured interviews with each participant that prompted them to evaluate students' mathematical understanding by watching short videos of a student reasoning about geometric conjectures. The entire study was conducted online through Zoom, and all activities were video recorded. In future data analysis, we will transcribe and code teachers' speech and gestures during the entire activities with the combination of human annotation and machine-augmented computational methods such as automatic audio transcription and automated coding based on regular-expression matching. Especially in addition to participants' verbal speech and gestures recorded through a personal laptop's built-in webcam, their body movement log data (e.g., skeletal joints' positions in space and time) will be automatically detected and tracked as numeric data points using a motion-sensing feature from a web-based toolkit [4]. For modeling, ENA was used to model and visualize multimodal interactions in a recent temporal context.

## 3 Preliminary and Expected Findings

In an earlier pilot study [1], we investigated the changes in the multimodal discourse of teachers formatively assessing students' embodied ways of mathematical thinking and reasoning before and after the embodied intervention, with attention to temporal sequencing. Employing QE approaches, we demonstrated that the qualitative and quantitative results aligned and validated each other. These findings suggest that we can model the multimodal interactions in light of temporal proximity by applying the analytical methodologies that we proposed. In our current investigation, we will apply this analytic approach to broader learning processes during the intervention. We will investigate teachers' multimodal interactions with peers and tools while they collaboratively create novel body-based actions to support student geometric reasoning. Teachers' body movement data can be used as a proxy for teachers' engagement with collaborative embodied activities. Using this proxy, it is possible to cluster teachers to examine how different multimodal discourse patterns they may represent in collaborative discussions. These quantitative movement log data will offer new ways to model nonverbal interactions and augment qualitative analyses.

## 4 Expected Contributions

With the aid of machine-augmented analytic techniques, this study may provide novel ways to "unfold" multimodal, collaborative interactions that we expect to be less laborious, more reliable, and with greater potential to be deployed at scale. Moreover, the visualizations of research findings using ENA can provide interpretable analytic information not only for researchers but also for teachers and students to track their progress and support formative assessment, which will help improve learning and teaching in practice. Lastly, this study will contribute to extending theoretical and methodological underpinnings for understanding complex meaning-making processes in CSCL contexts.

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# Symposia

# Initiating a Discussion on Reporting Practices in Quantitative Ethnography

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**Abstract.** Reporting is an essential aspect of all research, including the field of quantitative ethnography (QE), especially when using QE's flagship analysis tool, Epistemic Network Analysis (ENA). In this symposium, a disciplinarily diverse set of speakers who have collaborated on a systematic review of the QE field will assemble to share explanations and examples of how reporting features and practices specific to QE can enhance the understanding, transparency, and confirmability of research. Symposium attendees will be engaged in a dialogue on how to develop rigorous and widely accessible QE reporting guidelines as the discipline continues to develop.

**Keywords:** Quantitative Ethnography, Epistemic Network Analysis, Reporting Standards, Systematic Review.

## 1 Background

### 1.1 Quantitative Ethnography and Epistemic Network Analysis

Quantitative ethnography (QE) is a field that combines qualitative and quantitative methodologies to answer questions across a variety of disciplines. One commonly used tool in QE is Epistemic Network Analysis (ENA), a network analysis technique for analyzing the structure of connections among coded data by quantifying and modeling the co-occurrence of codes.

As QE is a nascent and also an interdisciplinary field, not only are its conceptual frameworks still actively expanding, but also its terminology. Definitions are still in need of negotiation in order to be adequately specific to carry meaning, but still plastic enough to employ across many disciplines. Part of this process also involves understanding what the critical decisions in a QE project are and knowing what and how to report from these.

### 1.2 Reporting Standards

Reporting standards guide what to report on from the myriad of decisions researchers make in a research project. Reporting on and justifying decisions researchers make aids the interpretability of a study and its findings, and transparency about crucial decisions also increases the confirmability of employed processes and results. Additionally, thoughtful reporting can help advance an entire field, as more consistent reporting and accessible standards can lower barriers to entry for new researchers and enhance comprehension from researchers outside the discipline.

As a QE community, it is our job to continue to define and update the reporting standards that we find most useful to understand, build upon, and respond to each other's work. Collaborating to establish reporting guidelines as a community can help strengthen our research and more effectively convey meaning in our work.

### 1.3 Foundational Work: A Systematic Review

Our inspiration for opening a conversation on reporting in QE comes from our work on a systematic review of QE publications. Since early 2020, an interdisciplinary team of researchers, including all symposium members, has performed a systematic review of over 100 publications from the QE Zotero library. Our aim was to understand how QE was being used across different disciplines and analyze reporting of several elements of QE research, mainly general information, open science practices, QE conceptualization and use, research design, data, sampling, coding, and segmentation. For a more detailed description on our methods and results, see: [1-2].

## 2 Symposium Aims and Structure

### 2.1 Aims

In this symposium, our goal is to contribute to an ongoing conversation about reporting in QE. Drawing from this project, as well as our own experiences as QE researchers and authors, we will discuss how specific elements of reporting have enhanced the interpretability and rigor of research we have interacted with, especially projects involving Epistemic Network Analysis (ENA).

Our symposium will strive to address and bring forward the following questions for ongoing discussion within the QE community:

- How do we define QE, and how does that influence our standards and norms of reporting?

- What are the elements of QE research the community feels most uncomfortable or uncertain reporting and how can we bolster understanding and comfortability with these elements?
- With researchers from such diverse academic disciplines, how can we create a communal language of reporting that is both rigorous and generalizable?
- How can we formally and informally continue this conversation on reporting standards in QE going forward with the goal of creating common guidelines?

There are several beneficial products that could come from these conversations and questions:

- Sharing results and observations from our work on the systematic review, so that participants understand which research elements are most commonly reported and unreported in QE, and why this is important.
- Providing an accessible overview for newer community members on important ENA-specific reporting elements that will allow their QE research to be understood by others.
- Opening a dialogue on what the critical aspects of QE reporting are, and even discussing the possibility of working collaboratively to draft a document or create a working group on guidelines in QE reporting.

### 2.2 Structure

As contributor expertise in the area of reporting is fluid and collaborative, we propose a synergetic presentation structure. While each scholar will be most informed about the area of reporting they studied during the systematic review (as noted in their bio), the flexible roles of review members prompts a collaborative approach.

We plan to cover each of the reporting topics our systematic review studied, as well as further explain why we chose those reporting elements to study and their particular importance to QE. We will then invite the audience to share their views on reporting and how the community should address it going forward.

Our symposium will consist of the following:

1. A 10-minute introduction to the systematic review and reporting in quantitative ethnography.
2. Three-to-five-minute summaries of each reporting topic and systematic review results or observations by each team member on their topic of expertise.
3. A 30-60-minute discussion with attendees on two main questions:
   (a) What do you consider the most important things to report on in your QE research and how do you report on them?
   What elements do you believe should definitely not be left out?
   Do you agree with the elements of reporting discussed in the presentation?
   (b) How can we continue and/or formalize discussions on reporting in the community (e.g., by creating a working group, a document of proposed standards, etc.)?

For the discussion, we plan to utilize polling (e.g., Mentimeter or similar) to help mitigate social influence while compiling responses and ideas and use those results to help structure the discussion as well.

## 3 Symposium Contributors and Topics

### 3.1 Contributors

Our symposium is comprised of eight contributors, each with an important contribution to the conversation of reporting. All contributors have worked and/or published in QE and, as a collective, provide a well-rounded group of scholars who are committed to advancing and improving QE, and who have had ongoing and rigorous discussions and debates on the definition and future of the discipline.

**Savannah Donegan.** Savannah Donegan is an MSc student in Philosophy and Public Policy at the London School of Economics and Political Science and has a BA in Economics and International Studies from the University of Wisconsin-Madison. During her time at the Epistemic Analytics lab, she worked and consulted on diverse QE research projects from 8 countries and 4 US states across 15 distinct institutions. Her focus on the systematic review team is on the reporting of QE conceptualization and use, as well as sampling.

**Diána Dunai.** Diána Dunai is pursuing a PhD in Interdisciplinary Social Research in the Doctoral School of Sociology at Eötvös Loránd University. Her topic is related to food salvage practices and motivations driving surplus food redistribution. Diana is new to QE and is learning about the methodology through participation in the systematic review. Her role in the team is coding on general information and open science practices and assisting research coordination.

**Brendan Eagan.** Brendan Eagan is the Associate Director for Partnerships and Community Engagement at the Epistemic Analytics lab at the University of Wisconsin-Madison. He has been involved in the development, refinement and application of many QE tools, including ENA. He has over five years of experience teaching and training researchers and acting as a consultant on research projects employing QE methods. He currently serves on a number of different committees for the International Society of Quantitative Ethnography. He has served in an advisory role for the systematic review.

**Rogers Kaliisa.** Rogers Kaliisa is a Doctoral Research Fellow in Learning Analytics at the Department of Education, University of Oslo, Norway. His research utilizes networked approaches (e.g., social and epistemic network analysis) and automated discourse analysis to study online learning environments. Rogers has been involved in a number of QE events, such as the data challenge, and recently as a facilitator for the QE Accelerator program. He currently serves as a member of the International Society of Quantitative Ethnography's communications group. His focus on the systematic review team is on data as well as study design and analysis methods reporting.

**Marcia Moraes.** Marcia Moraes holds a PhD in Computer Science and is currently a Computer Science Scholar at Colorado State University. Marcia started her work on QE in 2019, when she participated in the early career workshop. Since then, she has been working on the intersection of learning sciences, ENA, and learning analytics visualizations. Her focus on the systematic review team is on the coding process and its importance in contributing to future replication studies.

**Gjalt-Jorn Peters.** Gjalt-Jorn Peters is an Associate Professor of Methodology and Statistics at the Dutch Open University, and conducts research in methodology and health psychology, specifically behavior change. In 2017, together with Szilvia Zörgő, he started developing the Reproducible Open Coding Kit (ROCK), an open-source tool for the coding and analysis of qualitative data. His role in the systematic review team is mostly related to research design and managing the back end of the systematic review by leveraging the metabe for R package.

**Clara Porter.** Clara Porter is a research assistant at RAND Corporation focusing on health, human rights, and the environment. She holds a BS in Economics and Environmental Studies from the University of Wisconsin-Madison. She was formerly a member of the Epistemic Analytics lab, where she consulted on dozens of international QE research projects as well as being involved with the QE data challenge, helping to lead ICQE workshops, and co-authoring QE research in political psychology. Her focus on the systematic review team is article selection and segmentation.

**Szilvia Zörgő.** Szilvia Zörgő is an Assistant Professor at Semmelweis University, Hungary and a Marie Curie Fellow at Maastricht University, the Netherlands. Her previous research dealt with patient decision-making; her current project focuses on understanding how people search for and interpret health-related information online. Szilvia has been involved with QE since 2017 and is co-developer of the Reproducible Open Coding Kit (ROCK). Her role in the systematic review team centers on research design and general coordination of research activities, as well as coding on open science items.

### 3.2 Reporting Topics

**Reporting of General Information and Open Science.** Our systematic review collected data on basic information, such as institutional affiliations and the place of data collection, to determine the extent of international collaboration within the selected publications. In some instances, authors did not report where they collected data, which would have aided the general interpretability of research design and the contextualization of findings. We were also interested in the extent to which open science practices (specifically, open access, preregistration, publicly available data, and research process documentation) have been adopted within the QE community. Open science practices are potentially beneficial for increasing transparency and accessibility within the QE community.

**Reporting of QE Conceptualization and Use.** Continuing to define the meaning of QE and its applications in diverse research fields is one of the key goals of our community. Through the systematic review, we have had the chance to observe how researchers in fields from learning analytics, medical anthropology, educational psychology, and several other disciplines apply QE and ENA to their particular field of study. It may be advantageous to discuss more openly how we define QE and in what instances QE methods are warranted to answer research questions. From observations in our systematic review, we will give an explanation of why it is helpful and productive for researchers to reflect on and directly articulate their definitions of QE and ENA and why they chose to use them for their research. This kind of explicit reporting of their understanding and intentions not only makes their paper clearer and more rigorous but helps our community definition of QE evolve as we reach even more fields of study.

**Reporting of Research Design.** QE uses a range of conceptual and practical tools for sensibly analyzing big data and human behavior. This is because one of the key affordances of QE is that both qualitative and quantitative data can be represented in a unified dataset, which calls for the need to embrace different approaches in QE research. In our analysis of QE studies, we have found that the bulk of QE studies are using ENA, which is a flagship tool within QE. However, our analysis also shows that there is a growing trend of complementing ENA with other approaches. Some of these include descriptive and inferential statistics, topic modeling, social network analysis, and sentiment analysis. This can generate a more unified methodology for modeling learning processes and provide actionable insights for research and teaching practices. Reporting on details of not only ENA parameters but these mixed or non-ENA methods of analysis can help demonstrate exactly how ENA can be combined with other forms of analysis, or exactly how non-ENA analyses can extend our ideas of what QE is.

**Reporting of Data.** One of the key characteristics of QE studies is the explicit description of metadata, which is information about data that is used to group data providers in order to create various types of analyses and models [1]. Some of the examples of variables included as metadata in QE studies include timestamps, participant IDs, sex, sessions, and class numbers. Despite the value of metadata for QE analysis, the majority of authors in our review rarely include details about the metadata they collected. Given that QE and ENA often manipulate datasets according to different participant characteristics, reporting more on metadata could spur ideas for analysis as well as provide better information about the characteristics of participants or other phenomena of interest.

**Reporting of Sampling.** Sampling, and description of the sampling process, is an important element in many designs of empirical research. In QE, it helps form our understanding of how groups and networks will later be segmented or arranged. Metadata, descriptive features, and demographic characteristics of samples can all be used to arrange networks and provide another perspective on the results of research. Sampling works hand in hand with segmentation, study design, and other elements to provide meaning and different ways to analyze study data. Especially when trying to enhance the potential for other researchers to read, understand, and even build off QE research, it can be beneficial to be very specific about sampling methods, especially when working with ENA. For example, the size and qualities of study groups can be very influential in forming networks, and researchers doing similar work who are informed on detailed characteristics of a sample can more easily repeat, rearrange, or study disclosed results to inform their own work using ENA.

**Reporting of Coding.** While quantitative researchers use coding to count specific categories present in a quantitative survey and produce numerical patterns to confirm or disconfirm theoretical propositions [3], qualitative researchers code to find meaning in their data; discover themes, patterns, and processes; and make comparisons and develop theoretical explanations [4]. There are different ways that researchers can conduct the coding process, for example via a priori coding (also called deductive or top-down), inductive coding (also called grounded or bottom-up), or a mix of these approaches [3, 5]. Researchers then create a codebook to assist coders in the consistent application of the codes. Study designs may involve checking whether multiple coders, applying the same codes, agree on specific instances of those codes [6], such as using Cohen's kappa to calculate interrater reliability [7] or employing social moderation [8]. Besides interrater reliability, an important consideration may be intra-coder agreement: measuring the extent to which an individual applies codes consistently over a period of time [9]. The coding process could be supported by the use of software programs such as Excel, NVivo [10], ROCK [11], nCoder [12], and other algorithms to run fully automated coding process, such as topic analysis [13]. Reporting on these methods and decisions, together with justifications for employing them, can lend insight into how codes were developed, clarify what their definitions were (making them reusable or reproducible in other studies), and increase the confirmability of how groups or characteristics were defined from the researcher's perspective.

**Reporting of Segmentation.** While the information in a given line of data is important to any given qualitative analysis, the surrounding lines of data hold important information too for a QE analysis. In QE, the decisions researchers make to organize and format their data holds rich meaning. Segmentation is the organization of data so that analytic methods may make sense of the temporal context in the data given the presence (or absence) of a code or connection. In our systematic review, we looked at how researchers were making/writing decisions about five different components of segmentation: conversation, utterance, stanza window, stanza size, unit. Especially when using ENA, it can be difficult to make sense of an analysis without the reporting of these characteristics; for example, reporting unit selection is necessary to understand the different groups being compared, conversation and stanza window/size selection are key to understanding how that data was subdivided, and utterance is important for understanding what the analysis considered to be the smallest unit of meaning. It may be that authors excluded these pieces of information not intentionally, but because they do not adequately realize their importance toward understanding how the model was constructed. In any case, reporting on segmentation, especially when using ENA, is an easy way to make the analysis results more accessible and confirmable.

## 4 Summary

Opening a dialogue on the current state of QE reporting and its future will have many benefits for the community as a whole, from improving rigor to making QE research more transparent and comprehensible to those outside of the field. By engaging ICQE attendees in a structured but collaborative discussion, our symposium will not only encourage individual researchers to be more intentional and reflective in reporting, but also potentially spark the creation of reporting standards for the community as a whole. Employing the aims and methods we have elucidated, we hope this symposium will generate productive results for improving research rigor and transparency in the QE community.

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# Workshops

# Introduction to Automated Coding in QE

Jaeyoon Choi, Amanda Siebert-Evenstone and Seung Lee

This workshop will introduce methods for valid and reliable automated coding of text data using QE tools. During the workshop, participants will work individually and in teams to step through the process of creating an automated and validated code. In this interactive workshop, participants will learn how to (1) combine qualitative and quantitative perspectives for text analysis, (2) create codebooks for code validation and publication, (3) develop and test automated classifiers to code text data, and (4) validate automated coding schemes. We will also provide an R script for participants who wish to use the R package version of this technique.

# Advanced ENA Using rENA

Liv Nøhr, Daniel Spikol, Zachari Swiecki and Yeyu Wang

In this workshop, we will introduce participants to advanced features of epistemic network analysis (ENA) available in the rENA package for R, including weighted models, projection, masking, and trajectories. Our emphasis will be on how to implement the features, as well as how to determine whether they should be used. The workshop will culminate with an rENA analysis using ENA outputs in a subsequent technique, such as regression. Familiarity with ENA theory, the webtool, and rENA is preferred; however, we will provide brief overviews of each. We will also provide an R script for participants to use as a reference during and after the workshop.

# Advanced ENA Interpretations

David Williamson Shaffer and Amanda Barany

In this workshop, we will introduce participants to advanced features of epistemic network analysis (ENA) available in the webtool, including weighted models, projection, masking, and trajectories. Our emphasis will be on how to implement the features, as well as how to determine whether they should be used. We will provide brief overviews of ENA theory and applications of the webtool.

# The Role of Ethnography in Quantitative Ethnography

David Williamson Shaffer and Yotam Hod

In this workshop, we will focus on the central role that ethnography and qualitative understanding plays in meaningful application of QE methods. We will learn ways to avoid forgetting the E in QE analyses.

# Introduction to Epistemic Network Analysis

Yuanru Tan, Hazel Vega and Brendan Eagan

This workshop introduces the participants to the basics of the Epistemic Network Analysis (ENA) by analyzing two Shakespeare plays: Romeo and Juliet, and Hamlet. The goal of the workshop is to learn how to use the ENA web tool independently, and how to develop and interpret ENA graphs. The workshop consists of three parts: 1) theory, 2) step-by-step tutorial, and 3) group work. The topics of the first part are the differences between social network analysis and ENA, and data coding challenges. In the second part, the participants are introduced to the ENA web tool in order to compare the discourse between Romeo and Juliet, and Hamlet. Finally, the participants put their newly acquired skills into practice in the group work exercises.

# Open Science and the Reproducible Open Coding Kit (ROCK)

Szilvia Zörgő and Gjalt-Jorn Ygram Peters

The Reproducible Open Coding Kit (ROCK) was developed to facilitate reproducible and open coding, specifically geared towards qualitative research methods. Although it is a general-purpose toolkit, three specific applications have been implemented: an interface to the rENA package that implements Epistemic Network Analysis (ENA); means to process notes from Cognitive Interviews (CIs); and means to work with a decentralized construct taxonomy (DCT). In this introduction, first a general overview of the logic behind ROCK will be given, after which each of those three use cases will be discussed.

# Keynotes

# Fusing Qualitative and Quantitative Methods: Finding Moments to Savor in Slow Research on Adolescents

*Karin Frey*

Research Associate Professor, College of Education
University of Washington

How do we make room in our lives to savor research given publication pressures and the challenges of slow research? Creating reliable coding systems and negotiating conflicting goals among community partners can demand much of our attention. The talk will discuss how informal ethnographies and community participation complicate research questions and measurement in exciting and challenging ways. It will chart the introduction of QE and ENA into the discipline of developmental psychology by highlighting the potential for examining relationships within and between emotions, personal values, and behavior. The talk will describe a fusion between qualitative and quantitative methods that are used both iteratively and simultaneously. A journey that started with second-by-second coding of 600 students progressed to listening to adolescents provide complex explanations of their emotions, actions and moral identities. In recent research, in-depth self-examination of emotions seemed to promote unusually nuanced thinking about behavior and identity. This observation has stimulated the use of innovative methods to probe the potential of such explorations for adolescent's social and emotional development.

# Knowledge-Building Analytics: Quantitative Ethnography of Knowledge-Building Practices

*Jun Oshima*

Professor, School of Integrated Science & Technology
Shizuoka University

The knowledge-building theory is a new theory of learning from the knowledge-creation perspective. Because it emphasizes the collective nature of knowledge in the community, the traditional analytics approach is not appropriate to evaluate learners' practices. Instead, our research team proposes a new analytics approach to knowledge-building practices. First, we propose the socio-semantic network analysis of discourse to grasp how learners engage in their collective idea improvement. We developed application software for researchers to evaluate their discourse, Knowledge-Building Discourse Explorer. Researchers can visualize and examine the temporal trajectory of ideas learners discuss as a temporal network of words in their discourse. Second, in collaboration with the research group at Univ. of Wisconsin at Madison, we have been developing the knowledge-building analytics by integrating the socio-semantic network analysis and the epistemic network analysis. In the knowledge-building analytics, we examine how learners develop their collective ideas through epistemic actions (shared epistemic agency) in knowledge-building practices. In this talk, I discuss: (1) how our proposed analytics is connected to the epistemology, and (2) the history of the development of the methodological approach.

# Special Session

# Quantitative Ethnography of and for Policy and Practice

Juan Carmach, Sanna Järvelä, Mamta Shah, Nancy Wong, and Andrew Ruis

Moderated by Andrew Ruis, this special session brings together experts to speak on the application of Quantitative Ethnographic techniques in policy, education, healthcare, and digital anthropology contexts. Participants introduced their work and explored the ways they found QE compelling. Juan Carmach examined the ways that QE methods might prove compelling for UNESCO's global initiative to expand research in digital anthropology. Nancy Wong discussed her use of QE methods to understand how applicants for disability benefits understand their experiences. Mamta Shah discussed her work in corporate settings, where she engages in QE research on healthcare education and product design. Sanna Järvelä described how QE might serve as promising in work that examines how AI can contribute to self-regulated learning.

In any study of policy or practice, there are different constituencies with different and at times conflicting interests. Similarly, researchers may seek to improve processes or outcomes within an existing policy or practice even if they are critical of it. Speakers shared how to navigate tensions between different constituencies in policy and practice and discussed the ways they think about fairness in their work, specifically as it informs their QE approaches. They concluded with an exploration of the opportunities and challenges that the ease and scale of data collection has presented for their work on policy or practice.