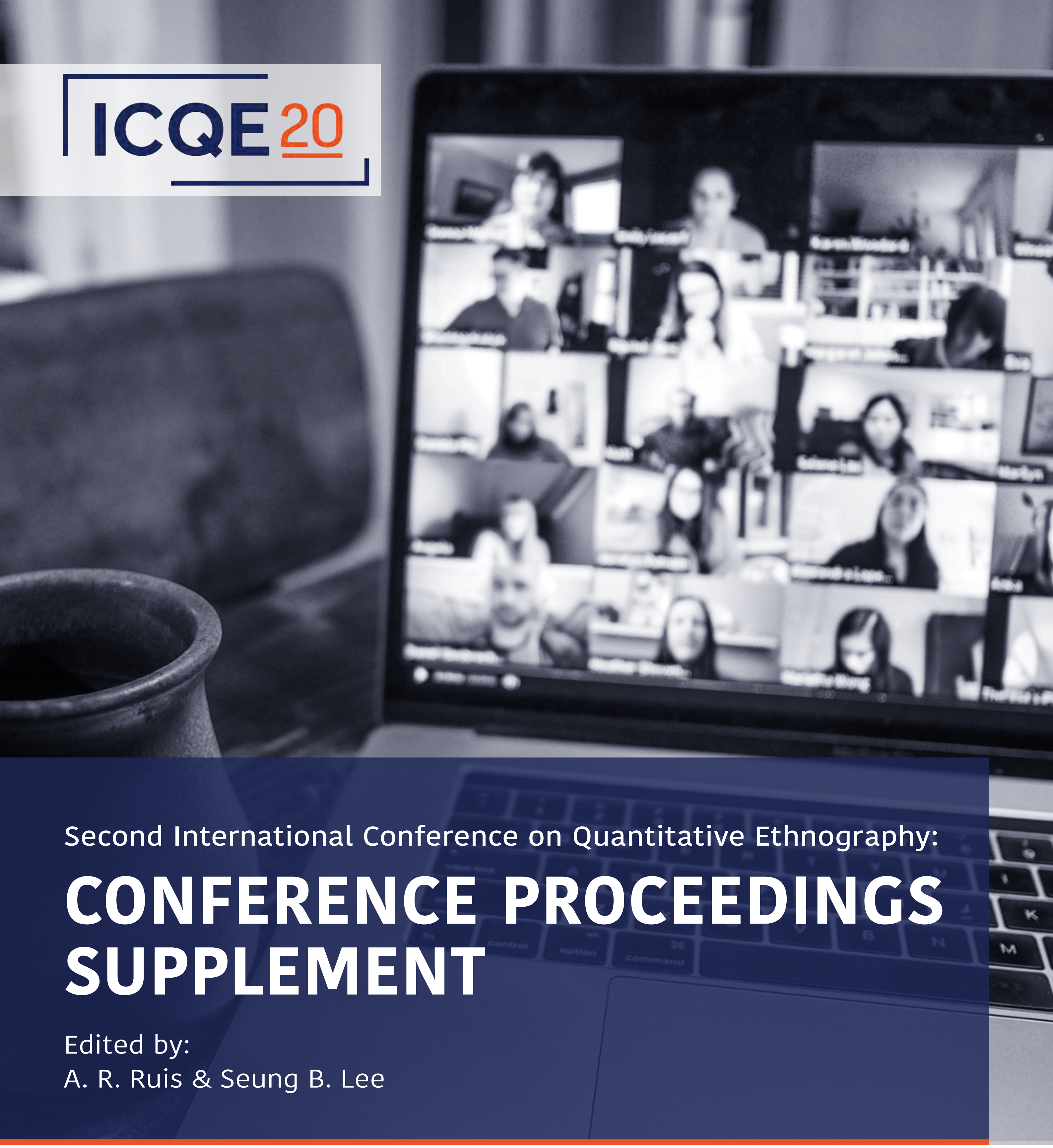

ICQE 20

Second International Conference on Quantitative Ethnography:

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Edited by:
A. R. Ruis & Seung B. Lee

1 - 3 February 2021
Online Conference

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Second International Conference on Quantitative Ethnography: Conference Proceedings Supplement

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Patterns of Individual Contribution to Idea Improvement in the Group Work Leading to High Learning-Outcome Groups

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Abstract. Idea improvement is a crucial process for learners to engage in productive collaboration. It has been found that (1) supporting learners to pay attention to idea promisingness would facilitate their engagement in improving their ideas through collaborative discourse, and (2) learners should be educated to hold appropriate epistemic frames to evaluate their ideas as promising otherwise their engagement does not lead to successful learning. Although the previous studies provided aspects of the process patterns leading to high learning outcomes, they have not yet thoroughly examined how learners in a group individually contribute to their group work. This study, therefore, attempts to dig into the issue by evaluating changes in the total degree centrality coefficients of vocabulary in individual learner's discourse exchanges as a contribution to the group discourse. Among 18 groups of first-year university students, two of each high and low learning-outcome groups were examined for identifying critical contribution patterns for high learning outcomes. Results revealed that high learning-outcome groups dealt with multiple ideas in different ways, simultaneously or sequentially. The patterns of individual contribution found in this study would help instructors to decide how to support learners in handling their multiple ideas for developing ideas based on their promisingness.

Keywords: Idea Improvement, Idea Promisingness, Individual Contribution.

1 Background and Research Purpose

1.1 Idea Improvement as a Crucial Process of Knowledge Building

Idea improvement is a crucial process for learners to engage in knowledge building. In the knowledge-building practice, learners should make a judgment of whether their ideas are promising and collaboratively improve them through knowledge-building discourse. Chen, Scardamalia, and Bereiter [1] examined if elementary school students could make their judgment of idea promisingness for their further improvement. The students collaboratively engaged in making judgments of their ideas based on their criteria of the improvability in Knowledge Forum [2]. They found that elementary students could develop their idea judgment criteria when being supported to continuously make judgments of their idea promisingness.

Students do not necessarily evaluate their ideas based on the same criteria of the idea promisingness. Blair and Mumford [3] identified the following aspects for university students to evaluate ideas as promising: (1) promising ideas should be understandable for everyone; (2) they should also provide immediate benefits; and (3) they should be consistent with common sense people hold. In their study, university students were not likely to take risky, time-consuming, and original ideas if they were constrained by time pressure. Thus, there are found individual differences in the evaluation criteria of the idea promisingness. Ikeda et al. [4] further examined how university students used their idea promisingness criteria in a project-based learning course by using the epistemic network analysis [5]. Their results revealed that idea promisingness toward successful learning included the aspects of an idea as challenging as well as reasonable. The interchange between the two aspects of idea evaluation might be crucial for instructors to support learners' engagement in creative work with ideas.

Another stream of research needed is to examine the process of idea improvement once learners identify ideas as promising. Kawakubo et al. [6] analyzed university students' progress reports in the Knowledge Forum during their participation in a PBL course. They applied KBDeX [7], a socio-semantic network analysis of vocabulary, for evaluating how students' ideas changed over time. They also used clustering analysis to categorize 18 groups by similarities in the vocabulary network structures. They found several conditions leading groups to higher learning-outcomes, such as productive and attractive proposals to their problems. One of their findings was that successful groups considered multiple ideas to decide which one could be promising.

1.2 Remaining Problems and Research Purpose

Although the studies provided aspects of the process patterns leading to high learning outcomes, they have not thoroughly examined how different learners in a group contributed to their group work. This study attempts to dig into the issue by evaluating changes in the total degree centrality coefficients of vocabulary in individual learner's discourse exchanges as their contribution to the group discourse. Among 18 groups of first-year university students, two of each high and low learning-outcome group were examined for identifying critical contribution patterns for high learning outcomes.

2 Method

2.1 Participants and Context

Seventy first-year university students engaged in PBL of creating their original happiness indices over 15 weeks. During weeks 5–14, they reported their progress in idea improvement, and then building their individual comments on their group reports each week in Knowledge Forum.

2.2 Collected Data and Analysis Plan

Evaluation of Learning Outcomes (Students' Final Proposals). Students presented their final ideas as posters in week 15. The authors with another graduate student evaluated their proposals by the seven criteria given to students as their poster preparation guidelines, with five-point Likert scales: (1) appropriateness; (2) uniqueness; (3) evidence (data); (4) interconnection between their ideas and evidence; (5) presentation of ranking of prefectures based on their indicators; (6) findings, and (7) discussion. The correlations across raters on their scores were significant (*r*s = .53~.91, *p*s < .05). Scores by each rater were standardized, and average scores across raters were used as the groups' idea scores.

Social Network Analysis of Vocabulary in Students' Written Discourse. The authors used nouns representing their ideas during a specific phase (weeks 9–14) when students examined their promising ideas and attempted to improve them. The nouns representing their ideas were identified by a cluster analysis proposed in Kawakubo et al. [6]. By using KBDeX, a socio-semantic network of vocabulary was created for each group. The authors then examined the temporal change in the total value of the *degree centrality coefficients*, a measure of the idea improvement, every time a report in the dataset was added. For further identifying individual contribution to the group discourse, the changes in the total value of the degree centrality coefficients in each member's discourse were compared with the group level of changes over time.

3 Results and Discussion

3.1 Selection of Groups for the Comparative Analysis

Based on their evaluation scores of final proposals, two high learning-outcome groups (A and B, their idea scores were 66.4 and 63.8) and two low learning-outcome groups (C and D, 38.7 and 34.8) were selected for the comparative analysis in this study.

3.2 Temporal Changes in the Total Value of the Degree Centrality Coefficients

Fig. 1 shows temporal changes in the total value of degree centrality coefficients by high and low learning-outcome groups with different members' contributions. Through the comparison between two types of groups, it was found that the values in high learning-outcome groups (A and B) increased through several phases over weeks 9–11, whereas those of low learning-outcome groups (C and D) slightly went down. The content analysis of written discourse suggests that high learning-outcome groups were engaged in discourse for considering multiple ideas from multiple members' perspectives. The low learning-outcome groups stayed with their single initial idea to improve.

Differences in individual contributions to the group discourse revealed that two high learning-outcome groups unfolded their discourse in different ways. In group A, group members' contributions as well as the group contribution were mostly overlapped with one another. It suggests that every member considered the same ideas simultaneously and sequentially scrutinized one idea to another. In group B, each member's contribution was idiosyncratic, suggesting that group members simultaneously discuss multiple ideas to identify their most promising ones. Groups C and D had similar patterns to A. However, the lack of increasing stages suggests that they didn't consider multiple ideas. The comparative analysis in this study could be concluded that learners in high learning-outcome groups examine multiple ideas either sequentially or simultaneously to produce unique and attractive proposals. Future studies are needed to examine what factors could influence groups to take the sequential and simultaneous trajectory of the idea improvement.

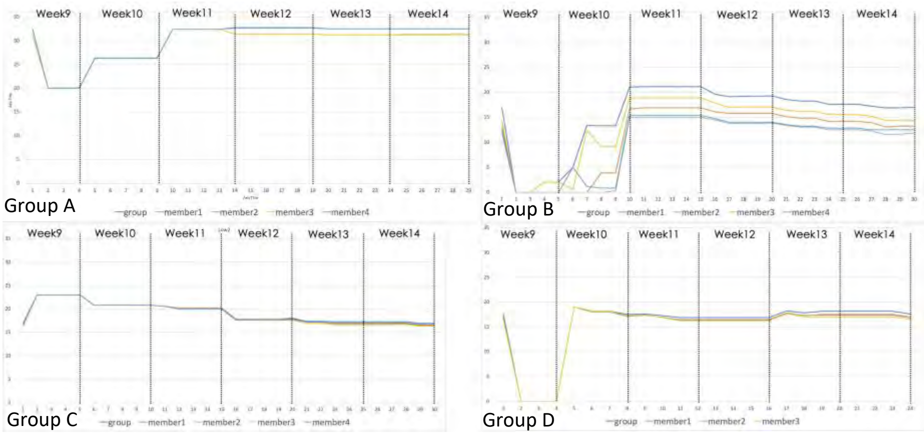

Fig. 1. Temporal changes in the total value of degree centrality coefficients by high (top) and low (bottom) learning-outcome groups.

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Exploring Computer and Software Engineering Students' Use of Websites Available on the Internet Using a Mixed Methods Approach

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Abstract. The appearance of the Internet has radically changed the way we socialize and access information. Nevertheless, despite research has suggested that student learning is influenced by the use of the Internet in different ways we know little about how students are using the different websites available on it to learn. This study aims at exploring the actions of computer and software engineering students' that are carried out on the Internet and that relate to practices of professional software developers. A literature review of common actions of professional software developers is used to design a survey that maps which of those same actions are also common among students and the websites used to carry them out. In addition, the frequency of use of these websites is also collected automatically from the web browser history using a custom-made software. I combine this data with course document data into a single Bayesian statistical model that is used to analyze the influence of the students' actions on their use of websites, of the academic calendar and also its variation in time. In addition, the model is used to cluster the students in order to compare them and to recruit participants for group interviews that further explore the affordances that the websites provide the students. I expect that the study will show that the students' use of websites is strongly related to the way professionals within their field use them. I addition, I anticipate that there will be important differences in the affordances that the resources provide to the students over time. The study will contribute to expand our understanding of how undergraduates use digital tools to learn, as well as to the digital ethnography research community by implementing methods that allow combining different types of data from different sources and contexts.

Keywords: Student Practices, Internet, Bayesian Statistics, Probability Clustering, Mixed Methods.

1 Introduction

The appearance of the Internet has radically changed the way we socialize and access information [9]. Now we can easily connect to several types of websites and with millions of other users from almost anywhere. Nevertheless, despite research has suggested that student learning is influenced by the use of information found on the Internet [4], we know little about how students learn when they navigate the web.

Moreover, while most of the websites students use are not included in course design, research also suggests that aspects like student engagement and self-regulated learning strategies are influenced by their use [8]. This study is part of a research project that explores the use of different websites available on the Internet by computer and software engineering (CSE) students that take part of software development courses in Norwegian higher education. More specifically, it gives attention to websites that are used in ways similar to those of professional software developers. These professionals rely on several websites for different aspects of their work [10] and CSE students have been observed capitalizing on those same websites during their academic tasks, even if they were not included in the design of their course [7].

To investigate the use of websites I consider them as part of the students' practices. Practices are considered here as arrays of actions, purposes and relationships with people and things, temporally and spatially arranged, that characterize the way people do things [3]. Practices can be embedded in common cultural, material and social arrangements, like for example a professional domain, higher education or even both simultaneously, and within one another, meaning that one practice can be the result of another practice. For example, a practice in the software development domain, like resorting to a specialized forum on the Internet to find other developers' inputs to solve a programming problem, could also be the place for different ways of learning.

This study focuses specifically on the actions that give shape to the students' practices. Actions characterize the interaction with the environment that takes place when a practice is enacted. In this interaction, different elements within the environment mediate the student's actions to achieve a certain purpose [9]. For instance, in the example above, the student's action was to access a specialized forum on the Internet (environment) to finds inputs from other developers (elements within it) that provided affordances (mediates) to solve a programming problem (purpose). These affordances will depend on both, the elements in the environment (what can be done with them) and the student (what she/he can do with them). For example, while one student might be able use the information found by implementing it directly in her/his own code, another student might develop her/his own solution based on critical features that she/he found within the same information. While both students solved the problem, the actions carried out in order to it were different. This study investigates the actions that characterize the students' practices by examining: *(1) What actions characterize the students' use of websites; (2) how the students differ in the affordances that the use of those websites provide them; and (3) how they differ in how the use of those websites unfold in time.*

2 Methodology

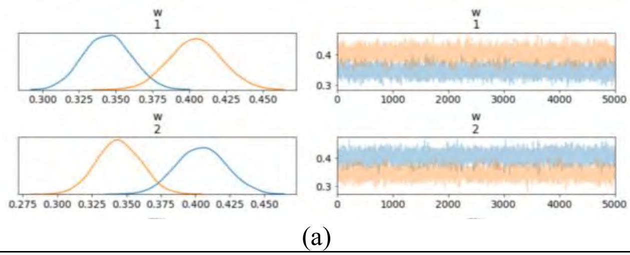
In order to explore the students actions that are similar to those of professional software developers and that are carried out on websites on the Internet I combine different types of data and methods. First, to relate the students' actions to those of professionals, I performed a literature review of actions that related to four main practices of software developers, defined based on the work of Nerland [6]. These practices are (1) solving programming problems encountered in software development projects, (2) staying up to date with trends in the software development industry, (3) learning new software development skills based on their personal interests and (4) managing their career profile. For example, one action carried out to stay up to date with trends in the industry was to reach specialized online communities in news aggregators to read relevant news [1]. Based on these actions, a survey instrument was developed to map which of them were also common among CSE students, and which websites on the Internet were used to carry them out.

The survey is set up on a custom-made software that, in addition, collects the frequency of use of each of the websites selected by the students from their web browser history. This is done automatically and from a three-months period back from the moment the survey is answered. The browser history information is used to operationalize the daily intensity of use of each website and is related to actions mapped in the survey by being combined with survey data. It is acknowledged that the websites can be used by the students in ways not considered by the actions mapped in the survey. To account for this, the strategy is to assume in the analysis that variance in that frequency is only partially explained by the mapped actions.

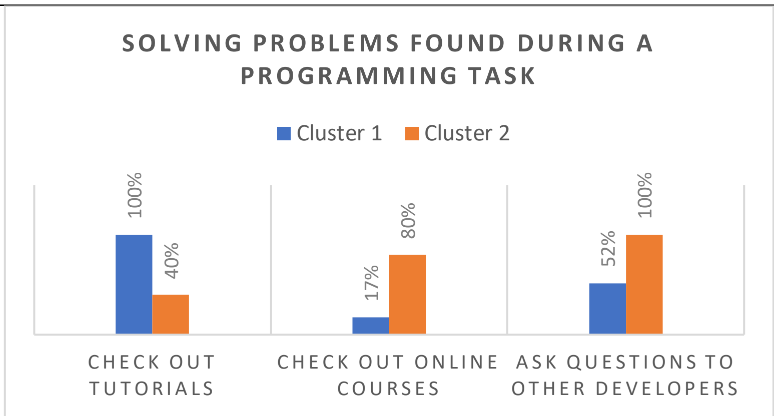
The survey instrument was tested in the Spring Semester 2020 in a bachelor level software development course in a university in Oslo. The survey was answered by 17 students and successfully mapped their actions and collected browser history data of the websites they declared to use. Before answering the survey, the students sign an informed consent, and were asked to check detailed information regarding the data to be collected and about the way it is stored. Data collection is scheduled for November 2020 in several CSE bachelor level software development courses in Oslo from different cohorts. I expect to collect between 200-250 responses.

The quantitative analysis and the clustering is implemented by combining a Poisson regression approach [3] with multilevel regression mixture analysis [5]. This approach allows explaining the variance in the frequency of use of the different websites in time based on the actions the students declare to carry out when using them. It also allows to include other data in different nested levels, like for example the activities in the academic calendar they had scheduled for each day. In addition, by using a mixture model, a latent categorical variable is included in the regression to cluster the students based on their latent behavior. The clusters can be later compared based on how time and the actions the students carried out in the websites affect the probability of them being used. An example of the output generated in the quantitative analysis to compare latent clusters is presented in Figure 1.

After the quantitative analysis and the clustering is performed, students belonging to each cluster will be invited to participate in group interviews. Between one to two groups consisting of 5-7 students from each cluster will be invited to participate. The group interviews will explore differences in the affordances that the use of the different websites provide the students and their relation to learning in higher education.



(a)



(b)

Figure 1. Some examples of the different analytical methods outputs. (a) An example of a comparison of distributions between clusters of two regression coefficients (w1 and w2), belonging to, for example, time and an activity within higher education. (b) An example of a graph comparing the frequency of three actions that the students declare to carry out when solving problems during found during a programming task in two clusters.

3 Expected Findings

In this study, I expect to find that students use the Internet in ways that are similar to those of graduates of their domain, and that this varies among students and over time. I anticipate that I will find that the use of websites on the Internet can provide different affordances to the students that are relevant for their learning, but that this differs among them. It is also possible that the study will show differences in the way the students are using the websites in time, and that for some students this unfolds in relation to how their courses in higher education progresses. I expect to see that all these differences will uncover different patterns among the students that will help characterizing their actions and their practices, and the way they take advantage of the websites available to them on the Internet.

4 Expected Contribution and Next Steps

This study contributes a more detailed analysis of how undergraduate students, specifically in CSE programs, use websites available on the Internet to learn. It contributes to the understanding of how digital technologies and the Internet influence and change the way we learn. In addition, the study contributes methodologically, by illustrating ways of collecting and analyzing data of students' online actions beyond the classroom boundaries. It also contributes to the field of quantitative ethnography by showing how Bayesian statistics can be used as a means to combine data from different sources and contexts (survey data, documents and browser history) to make sense of a complex phenomenon. In addition, it shows how clustering methods can be used in combination with qualitative methods purposively, in order to better explain the meaning of differences within results in quantitative analysis. The study is part of a larger PhD project that investigates higher education students' practices on the Internet; its results will be used as an input for a formative intervention in a subsequent study. The intervention will test ways of supporting the students when using websites on the Internet in the context of a software development course in a CSE program in Norway.

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Visualizing Hypothetical Outcomes in Quantitative Ethnography

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Abstract. There have been growing calls to make data and their underlying assumptions visible to end-users for transparency and deeper data insights. However, interpreting the visualizations associated with quantitative ethnography can be challenging. This paper describes an experiment that explores how a crowdsourced sample interpreted two different visualizations, one that uses network graphs and one that adds annotations for data uncertainty. Findings suggest design features that may highlight different data aspects to aid interpretation.

Keywords: Quantitative ethnography, Dataviz, Data uncertainty

1 Introduction

There have been growing calls for making data and their underlying analyses visible to users to increase trust and perceived relevance of data interfaces. However, interpreting visualizations of complex analyses is challenging. This is because viewers need statistical reasoning, prior knowledge of the data domains, and understanding of the uncertainties inherent in the data collection and analytic process (e.g., aggregation, prediction accuracy, etc.) [1–3]. These issues are even more present in interpreting visualizations associated with quantitative ethnography, whose underlying analyses are not always visible to users. While prior work offers design guidelines [3], there has been limited empirical research on how users make sense of different visualization aspects. This paper describes an experiment on how users interpret two different visualizations, one that uses network-based visualizations and one that adds annotation for data uncertainty.

2 The Need to Represent Data Uncertainty

Several challenges pertain to interpreting data visualizations. First, viewers need statistical and mathematical knowledge to understand the underlying analytic techniques and results [1,3]. Second, data visualizations carry implicit biases from the researchers [4]. In particular, for qualitative data, viewers who are not familiar with the data and analytic processes may not readily recognize which aspects of the visualizations to attend to [4]. Third, there exist uncertainties in the data processing pipelines that are often hidden from users [2,5].

The most common approach to visualizing uncertainties is use of extrinsic annotation, such as error bars, to indicate confidence or prediction intervals [6]. Another approach is to present a range of continuous outcomes, such as density plots or hypothetical, discrete outcomes, to make the distributional properties of the underlying data explicit [7]. These types of representations have been associated with improved prediction accuracy [8]. A common theme across these representations is (1) a focus on a range of possible outcomes and (2) use of annotations and interactivity to scaffold interactions with novel data types. These insights inspire this study's design to add annotation and uncertainty visualizations to quantitative ethnography. This paper explores the following question: **How do participants interpret quantitative ethnographic visualizations, with and without annotation for data uncertainty?**

3 Method

Participants Participants included 101 workers on the crowdsourcing platform Amazon Mechanical Turk (AMT). Prior research has found that surveying AMT is generally high-quality and demographically representative of the U.S. population [9]. The most common age group for participants in the current study was 25-44 (70.83%), followed by 45-64 (20.83%) and 18-24 (6.25%). 59.38% of participants reported having taken classes in statistics or data visualizations.

Fig.1. Visualization Conditions: (Only A) Network Graph; (A, B, C) Network + Data Uncertainties. Most frequent co-occurrences: collaboration-planning/monitoring

Procedures Upon accepting the crowdsourced task, participants were redirected to a web page containing instruction and survey questions. Participants first completed a 6-question test that drew from VLAT, a validated instrument for data visualization literacy [10]. Participants were then randomly split into two conditions: baseline (n = 56) and uncertainty (n = 55), to interpret "graphs about how a worker engaged in collaboration tasks based on their work log files."

The baseline condition saw a network-based visualization (produced through the Epistemic Network Analysis (ENA) web tool, [11]; panel A, Fig. 1). Meanwhile, the uncertainty group saw the same visualization in addition to representations for data uncertainty (panel A-C, Fig. 1). Similar to prior work that conveys uncertainties through visualizing a range of outcomes, the representations include examples of what the patterns may look like from a random sample (panel B) and from a range of samples (panel C). These representations suggest that the collaboration patterns may vary with data.

Consistent with measures in prior work on data uncertainties [2], participants in both conditions then answered the same questions for interpretation accuracy, trust, and usefulness: (1) What do you see about the patterns in the graphs?, (2) To what extent do you trust the visualizations reflect the reality of the worker's collaboration? [slider 0-100], and (3) To what extent are these types of visualizations useful to track your own task engagement? [slider 0-100]

Analyses Mann-Whitney-U tests suggested no significant difference in baseline understanding of data visualizations (*M* baseline = 3.79, *M* uncertainty = 3.47, $p = .12$). To assess interpretation accuracy, binary codes examined whether participants mentioned the representations' core ideas: task frequency, task cooccurrences, and variance. Task frequency indicated the extent to which different task (e.g., motivation, monitor, plan) occurred. Task co-occurrence was coded if participants mentioned links between two tasks (e.g., line between plan and collaboration). Finally, variance was coded when participants described patterns as concrete versus variable. An example answer that showed understanding of both data trends and variance: "patterns differ by week, but the task combination is consistent". Wilcoxon signed rank and Mann-Whitney-U tests were used to examine differences in interpretation, perceived trustworthiness, and usefulness.

4 Preliminary Findings

There was no difference between conditions in how often participants mentioned task frequencies and co-occurrences ($p = .15$, and $p = .19$, respectively). Most answers were descriptive of task frequencies, for example, "The employees most frequently plan, collaborate, and monitor in the same task.", without elaborating on task co-occurrences or implications of the work patterns. Notably, participants in the uncertainty condition more frequently noted data variance by pointing out that the work pattern "increased then decreased", "shifting", or "vary", phrases that rarely appeared in the baseline group's answers ($p = .01$; 16.28% Baseline, 43.40% Uncertainty). Participants did not significantly differ in reported trust that the graphs represented the reality of a hypothetical worker's experience (Baseline $M = 62.18$, $SD = 24.59$; Uncertainty $M = 65.36$, $SD = 19.32$, $p = .52$), or how useful they perceived the graphs (Baseline $M = 54.14$, $SD = 31.41$, Uncertainty $M = 56.58$, $SD = 24.12$, $p = .69$).

5 Discussion

Participants who saw the uncertainty annotations appeared to recognize data variance more than those who did not, even though there was no difference in time to task completion between the two groups. Such understanding is important because it helps users recognize the underlying data trends and make more accurate predictions [5,8]. This study did not find a difference in participants' reported trust or perceptions of the visualizations' usefulness. It is possible that these measures may be confounded by prior experience and effort [2]. Future research can explore these confounding factors by employing longer-term study designs. Overall, the current study offers promising directions for visualizations of quantitative ethnography:

1. What does designing for uncertainty of quantitative ethnography look like in time-constrained, everyday decisions? For example, how do we convey uncertainties in visualizing students' epistemic understanding for teachers who (1) may have little experience with how epistemic dimensions are coded, and (2) have to make in-time instructional decisions from the visualizations?

2. Given the varying levels of reported trust and usefulness in visualizations in this study (large SDs), how can we increase these measures as a pathway to better interpretation and future decision-making based on data?

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Using Conversation Analysis and Epistemic Network Analysis to Understand Social Presence in an Asynchronous Online Discussion

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Abstract. This study investigates how two different approaches, Conversation Analysis (CA) and Epistemic Network Analysis (ENA), can be used to understand how social presence contributes to knowledge construction in asynchronous online discussions. We are particularly interested in examining the interactive indicator to understand and unveil how those interactions occur, considering both the structure of dialogue and issues of power. Face-to-face interaction provides participants with immediate cues about each other's understanding; however, this is more difficult in online discussions based solely on text. We believe that this study is especially interesting now as many instructors are moving from face-to-face, where structure and power are pre-defined, such as lectures, to emergency remote teaching. Thereby, CA is applied to examine the role and process of social presence, while ENA is used to unveil the connections underneath that process. We applied both techniques to analyze the discussions on a master's level course discussion board. Our results show that both techniques bring different and complementary views to the analysis and should be used in combination.

Keywords: Asynchronous Online Discussions, Conversation Analysis, Epistemic Network Analysis, Online Social Presence.

1 Introduction

Considering that learning is primarily a social activity [Dewey, 1963, as cited in 1], asynchronous online discussions are a fundamental tool to facilitate social interaction in fully distant and blended courses in higher education [2]. The Community of Inquiry (CoI) framework, which is consistent with John Dewey's work on community and inquiry, emerged in the specific context of asynchronous, text-based group discussions, and aims to define how asynchronous online discussions shape student learning and their cognitive development [3]. Previous study that used CoI and Epistemic Network Analysis [4] provide quantitative and qualitative insights on the relationship between social and cognitive presence, missing are studies that examine how knowledge construction is supported by a close examination of these interactional patterns. This study takes a different approach by engaging Conversation Analysis (CA) to examine the role and process of social presence in an asynchronous online discussion and by using Epistemic Network Analysis (ENA) to unveil the connections underneath that process.

2 Methodology

2.1 Settings and Participants

The study was carried out in an online class for organizational leaders as part of a Masters of Education program at a Research 1, land-grant university, in the Fall 2017. A convenience sample of 24 working, adult learners were registered for the course with 19 consenting to be included in the research. The course focuses on the science of learning and includes an objective of developing connections between supportive learning theories and applying these supportive learning practices to course assignments.

2.2 Data Collection

The course had eight asynchronous online discussions. The data used for this study came from the first asynchronous online discussion. This forum was chosen because students were asked to discuss the contents of the class as a whole, not focusing on a particular learning theory. The dataset was extracted from Canvas and anonymized. The resulting dataset is composed of 77 postings.

2.3 Data Analysis

To understand how ENA extends the CA, we applied each of these methods in sequence. CA was conducted first, as it required a human coding and therefore hands-on approach to making sense of the conversations. Following CA, we employed ENA to reveal the interactive connections. To conduct the CA, we looked for the sequential organization of the discussion, considering a multi-party conversation [5]. We also used the concept of adjacency pair that "is composed of two turns produced by different speakers which are placed adjacently and where the second utterance is identified as related to the first" [6] (p. 115). Besides that, we also looked for the interactive indicators of social presence [7] in the data set.

To help with the analysis, we built a table that contains the following structure: sequential organization of the discussion, adjacency pair, interactive indicator of social presence, and reference to the actual post on the original data set. One author read the entire data set looking for those components to build the table. A second researcher did the coding considering the same parameters and codes to determine interrater reliability. Interrater reliability was established using Cohen κ, with all of the indicators reaching at least $\kappa = 0.94$.

After CA was conducted, we used ENA. ENA is a graphic-based analysis technique, which can be used to examine co-occurrences of concepts (codes) in a given segment of discourse data. Those co-occurrences are considered a good indicator of cognitive connections, particularly when they are frequent [8]. The connections among codes are derived from each unit of analysis (e.g., study subject) based on the code co-occurrences in the analysis in the data subsets called stanzas (e.g., sentence, paragraph, or document). Codes that occur within the same stanza receive a 1, and codes that do not co-occur in the same stanza receive a 0. In this study, each discussion message was coded with six binary codes capturing presence/absence of interactive indicators of social presence [7], and five binary codes related to new interactive indicators that emerged for the conversation analysis. Both units of analysis and stanzas were students (i.e., all student messages) and we used an infinite stanza window. That configuration enabled us to see for each student their connections between the interactive indicators of social presence.

3 Findings and Conclusions

The most frequently used interactive indicators were those related to appreciation and agreement with others students' postings. These kinds of interactions contributed to the sociability in this asynchronous online discussion. Sociability and trust are fundamental for an online discussion where knowledge is co-created [9]. Although most of the replies to students' threads consisted in expressing appreciation and agreement, all students without exception engaged in discussions, presenting their experiences, some asking questions, answering questions, completing ideas and expressing the desire to learn again from another student. Most of the students contributed to a collaborative knowledge construction by complementing ideas of others. We recognized those actions as new indicators of interactive category for social presence that foster collaboration.

In order to unveil the connections between the interactive indicators of social presence, we used ENA online tool [10] to represent the six codes of the original interactive indicators proposed by [7]: continuing a thread (CT), quoting from others' messages (QO), referring explicitly to others' messages (RO), asking questions (ASK), complementing, expressing appreciation (APP), and expressing agreement (AGR). We also used the five new indicators that emerged from our CA: suggesting materials (SUG), answering questions (ANS), complementing ideas (COM), expressing desire to learn again from one student (EXP), and creating a sub-thread (CS). Fig. 1 shows the relationship between all codes for all students group-average network graph.

Fig. 1 shows that the first component svd1represented by the x-axis explained 33.4% of the variance in the ENA created by the students, and the second component svd2 represented by the y-axis explained 19.9% of the variance. The thickness of the lines between the codes indicates the strength of connections; thicker lines indicate stronger connections, whereas thinner lines indicate weaker connections. The results obtained indicated that the x-axis (svd1) contained the most significant codes, CT (continuing a thread), COM (complementing ideas), APP (expressing appreciation), and AGR (expressing agreement), as identified by CA. While the y-axis (svd2) contained codes that were less representative, such as answering questions (ANS), quoting others' messages (QO), creating sub-thread (CS), asking questions (ASK), and expressing desire to learn from one student (EXP).

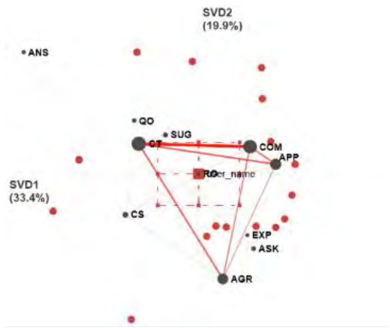

Fig. 1. Relationship between all codes for all students group-average network graph.

This study provided an opportunity to generate insights on how to apply CA and ENA to asynchronous online discussions by analyzing the interactive category of the social aspect of CoI. As mentioned before, previous works did not address that topic. We could observe that CA and ENA are complementary analysis techniques that can contribute to a broader understanding of the phenomenon of how interactive indicators can contribute to collaborative knowledge construction.

As future work, we intend to use ENA to build a model that represents how students are connecting the content that is being discussed in this asynchronous online discussion and compare that with the ENA interactive indicators model to analyze how the interactive indicators are related, or not, with the content connections.

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Using Epistemic Network Analysis to Help Instructors Evaluate Asynchronous Online Discussions

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Abstract. Discussions have been widely used in face-to-face, blended, and online learning as a way to facilitate the social construction of knowledge and to promote critical thinking. However, instructors lack the tools to assist them to monitoring and evaluating these discussions when they occur asynchronously online. In this paper, we propose the use of Epistemic Network Analysis (ENA) to help instructors evaluate these discussions by unveiling what concepts students are discussing as well as the relationships that they are building among those concepts. Findings indicate the application of ENA is a beneficial tool for evaluating students' online discussion participation and provides insight into the connections students' are making including their integration of course concepts with practice.

Keywords: Asynchronous Online Discussions, Epistemic Network Analysis, Evaluation Tool, Distance Education.

1 Introduction

Asynchronous online discussions is a commonly used strategy to maximize the quality of online learning experiences by facilitating the social construction of knowledge and promoting critical thinking [1]. However, not all participations and interactions demonstrate in-depth reflections and contribute to a meaningful social construction of knowledge. In addition, instructors lack tools to assist them in monitoring and evaluating activities on asynchronous online discussion, and because of that they felt overwhelmed [2]. In order to assist instructors to evaluate the contributions of individual students in asynchronous online discussion, we propose the use of Epistemic Network Analysis (ENA) to unveil what concepts students are discussing as well as the relationships that they are building among those concepts.

ENA is a network analysis technique that supports thick descriptions based on Big Data about learning to assess learner performance [3]. The theory that supports ENA is the epistemic frames, which understand expertise in complex domains as a network of connections among codes assigned to different elements of collaborative discourse (such as knowledge, skills, values, and decision-making processes) [3]. ENA has been used in several domains [3], and one of those is online asynchronous discussion. Unlike the work of Mello and Gašević [4] that analyzed how different configuration of ENA parameters influence students interaction in online discussions, this study explores how

ENA can be used to unveil concepts and concepts' connections that students are using to help instructors to evaluate asynchronous online discussion. This study has the overarching question: how can ENA be used to show the connections that students are making, in an asynchronous online discussion, between the concepts that are being learned?

2 Methodology

2.1 Settings and Participants

This study was initialized in an online class for organizational leaders as part of a Masters of Education program at a Research 1, land-grant university, in the Fall 2017 semester. A convenience sample of twenty-four working, adult learners were registered for the course with 19 consenting to participate. The course focuses on the science of learning and includes an objective of developing connections between supportive learning theories and applying these supportive learning practices to course assignments. The course is hosted on the Canvas Learning Management System of the university.

2.2 Data Collection

The course had eight asynchronous online discussions. For this study, we used data from the first asynchronous online discussion, because, on this board, students were asked to discuss the contents of the class as a whole, not focusing on a particular learning theory as in the other discussions. The data set was extracted from Canvas using a Python application developed by the authors. The resulting data set is composed of 77 anonymized postings.

2.3 Data Analysis

ENA is a graphic-based analysis technique that identifies and measures connections among elements in coded data [3]. The connections among elements are derived from each unit of analysis (e.g., study subject) based on the code co-occurrences in the data subsets, called stanzas (e.g., sentence, paragraph, or document). Codes that occur within the same stanza receive a 1, and codes that do not co-occur receive a 0. From the code co-occurrences, ENA produces, for each unit of analysis, a network, which capture the relationships between the different codes. The centroid of an ENA network summarizes the network as a single point in the space. This allows comparison among different networks because centroids located close together represent networks with similar patterns of connections, while centroids located far apart represent networks with different patterns of connections [5].

To answer our research question, we used ten "a priori" codes that represent the concepts that the students were learning and therefore the concepts that the students should connect in that online discussion to code the data, and generate a "well-formatted table" [3] for ENA. Those codes are: concept of learning (concept), retrieval practice (retrieval), space out practice (space), interleaving, elaboration, illusions of mastery (illusions), effortful learning (effort), beyond learning styles (beyondLS), growth mindset (mindset), and reflection of theory in practice (reflection). Two coders established an interrater reliability using Cohen κ, with all of the codes reaching at least κ = 0.74. As we are interested in the individual student's network of concepts, both units of analysis and stanzas were students (i.e., all student messages) and we used an infinite stanza window. That configuration enabled us to see for each student his/her connections between the codes previously described.

3 Initial Findings

To unveil the connections between the codes, we used ENA online tool [6]. Fig. 1 shows the relationship between all codes for all students group-average network graph.

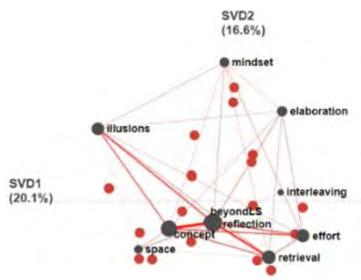
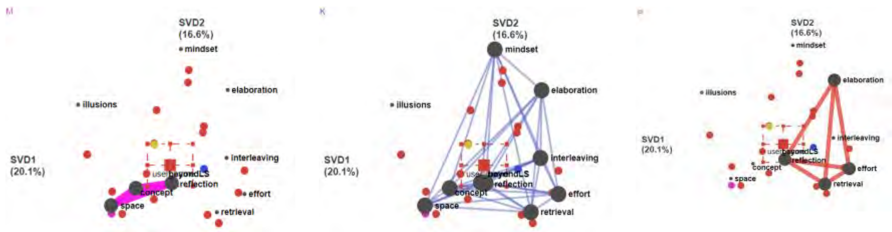


Fig. 1. Relationship between all codes for all students group-average network graph.

Fig. 1 shows that the first component svd1 (singular value decomposition 1) represented by the x-axis explained 20.1% of the variance in the ENA created by the students, and the second component svd2 (singular value decomposition 2) represented by the y-axis explained 16.6% of the variance. The thickness of the lines between the codes indicates the strength of connections, thicker lines indicate stronger connections, whereas thinner lines indicate weaker connections. The results obtained indicated that the most significant codes were reflection of theory in practice (reflection), concept of learning (concept), retrieval practice (retrieval), illusions of mastery (illusions), and effortful learning (effort). The stronger connection was between concept-reflection (0.27), retrieval-reflection (0.21), illusions-reflection (0.17), effort-reflection (0.16), concept-effort (0.16), concept-illusions (0.15), concept-retrieval (0.14), and retrieval-effort (0.12).

After analyzing each individual network, with the exception of two students (L and M), we observe that all students made connections that involved the reflection of theory in practice, meaning that they are thinking about how to integrate the concepts that were learned with their practice. As explained before, centroids located close together represents networks with similar patterns of connections. We could observe that most of the centroids are dispersed along the space, with fewer centroids that are close together, meaning that most of the students have different ways of connecting the codes, as shown on Fig. 2a, 2b, and 2c. In addition, our analysis exposed that there are students that mentioned fewer concepts but made stronger connections between them (Fig. 2a and 2c), while others made thinner connections among almost all concepts (Fig. 2b). In fact, student K (Fig. 2b) was the student who made the most connections between codes. The only code they did not connect was illusions of mastery (illusions).



a) Student M b) Student K c) Student P

Fig. 2. Examples of individuals ENAs.

4 Conclusion and Future Works

The initial findings show that using a student as a unit and considering every student's postings in an online discussion, as an infinite stanza, is a way to produce visualizations that represent individual student's connections between concepts. We believe that, by explicitly showing those concepts and connections to instructors, we can provide them with a tool that may help evaluate students' contributions in online asynchronous discussions. As future works, we intend to present the ENAs to the instructor to get feedback on the potential use of it in class. In addition, we will use nCoder [7], to build an automated coder to help in the coding process.

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News Media Communication of Risk and Mitigation Factors During Early Stages of the COVID-19 Pandemic

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Abstract. This study examines how risk and mitigation factors for COVID-19 on an individual level were communicated through online news articles from January to March 2020. Overall, there was a shift from risk factors in January to more connections with mitigation factors in March, indicating initially mixed understanding of the virus spread and lack of concern for mitigation measures.

Keywords: COVID-19, risk factors, mitigation factors, news media, communication

1 Introduction

The worldwide COVID-19 pandemic fostered confusion, misinformation, and fear. With no available vaccine or clear understanding of which medical treatments were most effective, people eagerly awaited path-forward updates from their governing bodies and the medical industry [1]. This called attention to what news outlets conveyed as the risks and spread of the virus and what recommendations they published.

How has the understanding of COVID-19 evolved, and how was this communicated in mainstream news sources? Communication in crisis needs to be both instructive and adjustive to allow people to understand how to behave for personal protection and help manage uncertainty [2]. This research evaluates published articles from various news sources to determine how COVID-19 mitigation and risk factors at the individual level were communicated in the early onset of the pandemic.

2 Methods

This study analyzes 101 news articles related to COVID-19 that were published online by the Associated Press (AP), British Broadcasting Corporation (BBC), Boston Globe, and USA Today between January 1 and March 31, 2020. The construction of the analytical corpus involved several steps. First, a dataset containing the titles, links, and snippets of more than 1 million online news articles related to the novel coronavirus was downloaded from the Global Database of Events, Language, and Tone (GDELT) Project (www.gdeltproject.org), a platform monitoring news media globally. After filtering for the sources and dates specified for the analysis, nCodeR was used to identify articles containing terms associated with risk and mitigation factors. From this subset, between 1 and 3 articles were selected from each week to ensure a balanced distribution across the 3-month period, resulting in 29, 33, and 39 articles respectively from January, February and March of 2020. The following number of articles were drawn from each news outlet: AP (30); BBC (20); Boston Globe (20); and USA Today (31).

The articles in the corpus were coded for 7 risk factors and 8 mitigation factors as defined by the codebook in Table 1. Each risk factor in the text was annotated with a code indicating if it was deemed to present (a) no or little risk or (b) moderate to high risk. Similarly, each mitigation factor was coded to specify whether it was (a) not considered efficacious, (b) suggested practice, or (c) enforced through laws and policies. Coding of each article was carried out by two raters. Epistemic network analysis (ENA) was then used to examine the pattern of connections between risk and mitigation factors discussed in the articles. For this analysis, an article was defined as both the unit of analysis and conversation. Co-occurrences of factors across the entire conversation were included in the model. A minimum edge weight threshold of 0.3 was applied to highlight the most salient connections in the network.

Table 2. Codebook of risk and mitigation constructs used in analysis.

Type	Construct	Definition
Risk	Droplet	Risk of infection from droplets (e.g. through coughing, sneezing)
Risk	Crowd	Risk of infection from being in a group or crowd
Risk	Contact: Symptom	Risk of infection from close interaction (proximity, contact) with someone with evident symptoms
Risk	Contact: No Symptom	Risk of infection from close interaction (proximity, contact) with someone without evident symptoms; including super spreaders
Risk	Surface	Risk of infection from surfaces (any kind, but generally hard)
Risk	Animal	Risk of transmission/infection from animals
Risk	General	General risk to population
Mitigation	Hand Hygiene	Handwashing, use of sanitizer, not touching one's face
Mitigation	Surface Cleansing	Surface cleaning
Mitigation	Sneeze Cough	Sneeze, cough protocol
Mitigation	Social Distance	Social distancing (includes "safer at home" recommendations and/or measures)
Mitigation	Face Cover	Face covering
Mitigation	Iso Symptom	Self-isolation if symptomatic

Mitigation	Iso Exposure	Self-isolation if contact with positive person or suspected positive person(s)
Mitigation	Avoid Travel	Avoidance unnecessary non-local travel (in general as well as to affected areas)

3 Results

The results indicate an overall shift in news media coverage of the risk and mitigation factors associated with COVID-19 from January to March 2020. Figure 1 displays the ENA plotted points (circular dots in lighter color) for the news articles and the group means (squares in darker color) for each of the three months, with the 95% confidence intervals represented by the box around the group means. A two-sample t-test assuming unequal variance showed that along the x-axis, January (mean=-20, SD=0.30, N=29) was statistically significantly different at the alpha=0.05 level from February (mean=0.03, SD=0.35, N=33; t(59.91)= -2.73, p=0.01, Cohen's d=0.69) as well as March (mean=0.12, SD=0.28, N=39; t(59.09)= -4.47, p<0.01, Cohen's d=1.10).

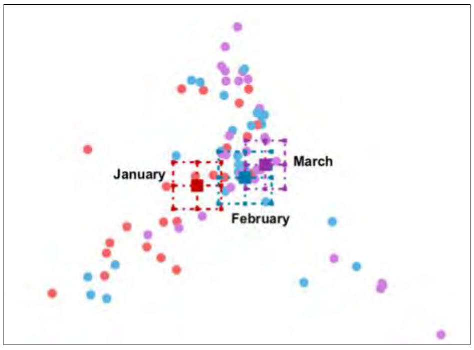

Fig. 1. Plotted points, means, and confidence intervals of news articles by month

Overall, Figure 2 presents the mean network models for each of the three months, respectively. In January, prominent connections can be observed among several contradictory risk factors, which seem to point to diverging viewpoints held around the coronavirus at the time. Strong connections are visible not only between the high risks for infection through animals (R.Animals.Y) and close contact with symptomatic individuals (R.ContactSymptom.Y), but also with minimal risks for the general public (R.General.N) and symptomatic transmission (R.ContactSymptom.N). Other connections in the network include the risk of infection via droplets (R.Droplet.Y) as well as recommendations for mitigation through hand washing (M.HandHygiene.Rec), cleaning surfaces (M.SurfaceClean.Rec) and the wearing of face masks (M.FaceCover.Rec).

The network model for February shows relatively strong linkages between a low risk for the public (R.General.N) and recommendations for mitigation through the practice of personal hygiene (M.HandHygiene.Rec, M.SneezeCough.Rec). However, the suggestions for hand washing are also associated with the views that face coverings are ineffective (M.FaceCover.NoEffect). At the same time, the relationship between the enforcement of social distancing measures (M.SocialDistance.Enf) and the quarantine of individuals exposed to the virus (M.IsoExposure.Enf) is more prominently visible, along with a connection indicating that there is little risk for asymptomatic transmission (R.ContactNoSymptom.N).

In March, the strong connections can be observed among key mitigation measures, including hand washing (M.HandHygiene.Rec), social distancing (M.SocialDistance.Rec, M.SocialDistance.Enf), and the isolation of exposed individuals (M.IsoExposure.Enf). In addition, social distancing is associated with the high risk of transmission through droplets (R.Droplet.Y) and in crowded spaces (R.Crowd.Y). Similar to the February network, asymptomatic infection (R.ContactNoSymptom.N) is portrayed as having minimal risk.

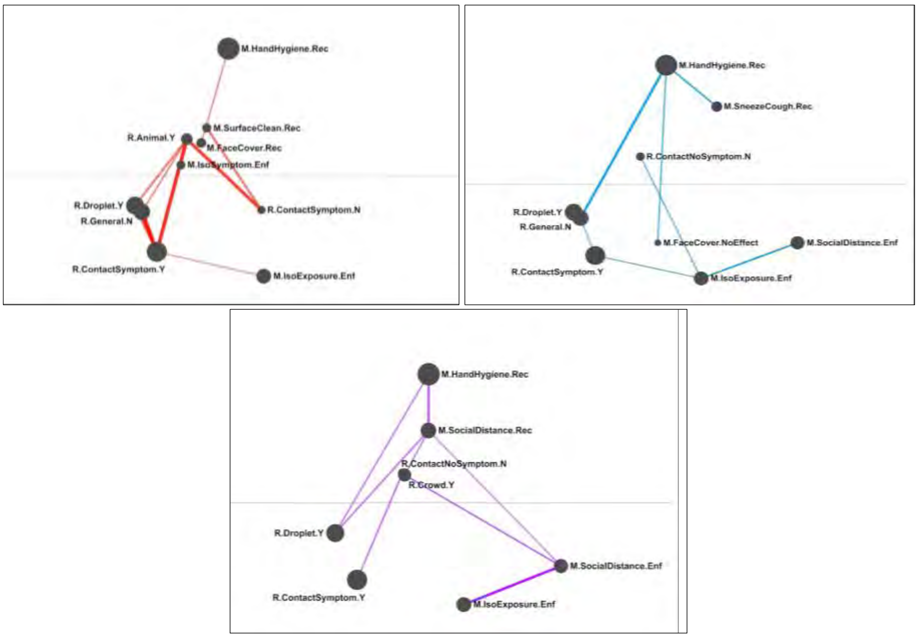

Fig. 2. ENA models of risk and mitigation factors from January (top left), February (top right), and March (bottom right) 2020.

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Network Analysis of COVID-19 Tweets between Donald Trump and Centers for Disease Control Twitter

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Abstract. This paper compares the leadership response to the COVID-19 pandemic of the Centers for Disease Control and Prevention (CDC) and the President of the United States of America, Donald Trump. The objective was to determine how COVID-related tweets of Mr. Trump vary from that of the CDC within the timeframe of January to April 2020. We used an inductively developed code system to deductively code data scraped directly from Twitter; nCoder was employed to automate the coding process. In order to compare the narratives under scrutiny, we generated network models with Epistemic Network Analysis. We were able to conclude that the CDC remained fairly consistent with their underlying concerns surrounding COVID-19, emphasizing the connection between education, protection and distance. The President, on the other hand, changed his narrative significantly over the course of these months, initially emphasizing collaboration, economy, and protection, then subsequently shifting to education, protection, and collaboration, as the COVID situation intensified. This work could inform how the lack of a unified message about the COVID situation from prominent leaders influenced the course of the pandemic within the United States and lend insight into future best public health practices.

Keywords: Quantitative Ethnography, COVID19, Twitter.

1 Introduction

In late 2019, COVID-19 emerged, eventually leading to a global pandemic in 2020. The pandemic altered all aspects of life including parenting [1], mobility of individuals within their communities [2] and social media usage [3]. Furthermore, the pandemic has forced people to reckon with science knowledge as it is necessary to make personal decisions regarding issues such as mask-wearing [4]. In response to the COVID-19 pandemic, the International Society for Quantitative Ethnography organized a community COVID data challenge in Spring 2020. The challenge sought to address the global pandemic by “help[ing] the world make sense of how people are reacting to the crisis, how those reactions are changing over time, and in response to events, how those responses are differing over time or between places” [5].

The authors of this paper were assigned to work together during this challenge as Team 7. Notably, other than our general interests in quantitative ethnography (QE), our team did not have any obvious crossover. Rather, our backgrounds represented business, engineering, anthropology, and learning sciences/biology. Although collaborating across disciplinary lines can be challenging [6], we were able to learn from one another and each made a unique contribution to our project. We explored the COVID-19 related content of Tweets from President Donald Trump and the Centers for Disease Control (CDC) from January-April 2020, the time period when the COVID-19 threat was expanding and reaching pandemic status. Our goal was to compare COVID-19 related messaging and content between Mr. Trump and the CDC from January-April 2020, when the pandemic was growing in severity.

2 Methods

First, we scraped Twitter data from @RealDonaldTrump and @CDCGOV from January-April 2020 using the Tweepy Python library (tweepy.org). We qualitatively reviewed Tweets from both accounts that used #COVID19 or #coronavirus to develop themes. We then inductively developed our codes and loaded our final seven codes and associated classifiers (Table 1) into the nCoder webtool (www.n-coder.org). All codes were then validated with two coders, and the final data set was uploaded to the Epistemic Network Analysis webtool (www.epistemicnetwork.org) to generate networks.

Table 3. Inductively generated code tree

Code	Key words/phrases
Protection	Protect, protection, prevent, prevention, precaution, play it safe, slowing the spread, slow the spread, wash hands, wash your hands, don't touch your face, do not touch your face, spread, stop the spread, personal protective equipment, ventilator, mask, shield, face shield, gloves, sanitizer, hand sanitizer, alcohol
Stress	Stress, stressed, anxious, worried, nervous, scared, scare, worry
Education	Learn, tips, support, stay connected, stay informed, follow guidelines, guidelines, awareness, aware, education
Distance	Avoid, avoid travel, don't travel, community transmission, travel, non-essential travel, keep your distance, practice social distancing, social distancing, physical distancing, stay at home, distance
Economy	Revenue, economic growth, investment, SBA, manufacture, PPP, EIDL, paycheck protection program, paycheck, small business administration, CARES act, funding
Testing	Analysis, testing sites, testing, tests, testing kits
Collaboration	Meetings, attending meetings, state governments, local governments, negotiations, coordination, thank you, good job, doing well, hardworking, hard work

3 Results

We found that although the CDC's messaging regarding COVID-19 stayed consistent over time, Mr. Trump's message changed between January and April 2020 (Fig. 1). From January 15-February 15, when the first official reports of COVID-19 infection occurred in the United States, Mr. Trump's Tweets mainly focused on the economy, collaboration, and protection, suggesting that the president's main concerns were on the economy and collaborating with other governmental officials, rather than educating citizens about the virus. In contrast, the CDC was tweeting about education, protection, and distancing measures, suggesting a greater focus on public health messaging and education. Testing became a higher focus for both entities over time. However, the general structure of the CDC networks remained relatively consistent over time. Mr. Trump's network looks more like the CDC's network by March, although a strong emphasis on collaboration is maintained.

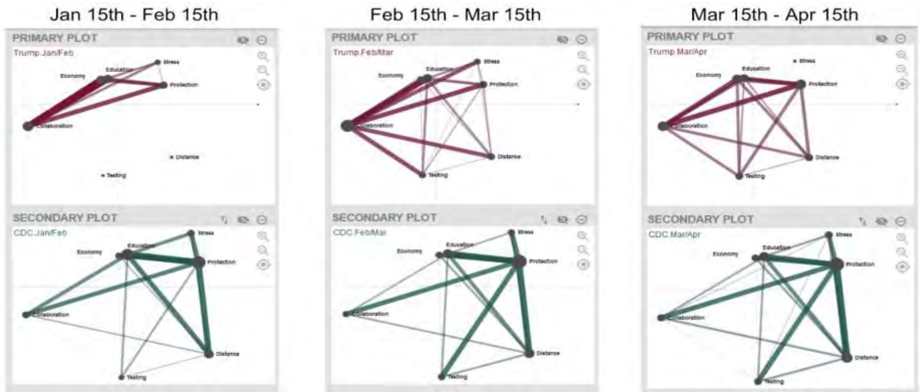

Fig. 1. Networks for @RealDonaldTrump (red) and @CDCGOV (green) by month.

4 Discussion

Our main finding was that during the initial phase of the pandemic, Mr. Trump and the CDC did not present a similar message. Over time, the messages between Mr. Trump and the CDC became more aligned. This may not be a terribly surprising result given the respective roles of the President and the CDC in the pandemic, namely that it may be expected for the President to be more concerned with collaborative meetings between governmental officials. However, the slow response by the President to present a unified message with the leading governmental agency responsible for the pandemic is notable. This could be a reflection of challenges associated with real-time management of social mobilization activities [7] or the politicizing of a public health issue [8]. One possible extension of this work is to examine long term economic and health impacts of countries that had a unified message from the beginning of the pandemic, and those who did not.

A limitation of this work is that the brevity of Tweets and limited accessibility to context (e.g. re-tweets, comments, likes) thereby limiting our interpretation. To maximize the exploratory phase of our research, more sets of inductive codes and more rounds of triangulation could have been performed. One future direction of this work is to examine responses to public health messaging from either the CDC or World Health Organization (WHO) to understand public engagement and reactions to health information.

Overall, we felt that the COVID-19 data challenge was a productive and valuable learning experience. Our team successfully overcame challenges associated with interdisciplinary collaboration and each person was able to contribute their own expertise and talents to producing results within a week. We recommend that others interested in similar work to identify roles early on in the process (which is recommended for successful interdisciplinary collaboration; [6]), to work in real-time with one another as much as possible, and to invest extra effort at the beginning of the process to collaboratively generate a research question that fits the constraints of the available data and any pertinent time limitations.

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Hierarchical Epistemic Network Analysis

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Abstract. We propose an extension to epistemic network analysis (ENA) that enables researchers to model the nested effects of multiple grouping variables in an ENA context.

Keywords: Epistemic Network Analysis, Linear Modeling.

1 Introduction

Epistemic Network Analysis (ENA) models discourse as networks of cotemporal connections between qualitative codes [1] by constructing a high-dimensional space of networks and projecting the space to reveal patterns of interest between the networks. Critically, ENA co-registers the projected *ENA space* with network graph representations of the original networks. As a result ENA can: compare the discourse networks of many individuals at once; allow statistical comparisons of networks; and provide a visual interpretation of *how* networks differ.

One of the most powerful mathematical features of ENA is a *means rotation*, which allows researchers to choose a binary variable of interest (usually a grouping variable), and constructs a representation that shows the maximum difference between the means of two groups. However, researchers are often interested in investigating more than one variable at a time, and there is currently no way to define an ENA space so that it shows the independent impact of multiple variables.

In what follows, we propose an extension to ENA, *hierarchical epistemic network analysis* (hENA) that makes it possible to analyze networks with a hierarchical set of nested variables such that the successive axes of ENA space show the impact of each variable independent of the preceding variables.

2 Proposal

In ENA, networks are represented in a high-dimensional space, C, where C_{ij} is the ith network's strength for the jth possible connection.[1]

$\dot{C}$ is a two-dimensional projection of C that highlights properties of interest among the networks. ENA produces the projection $\dot{C}$ by doing a means rotation to produce dimension that represents the biggest difference between two groups, followed by a

[1] Each j represents the pairwise connection between two codes in the ENA model.

singular value decomposition (SVD) to identify a dimension that accounts for the most remaining variance.

In other words, $\dot{C}$ is a two-dimensional, orthogonal plane within C into which the points of C are projected. *hENA provides an alternative way to construct that plane*.

To see how hENA works, let us assume that G and K are two mean-centered binary variables of interest in the data.[2] In ENA, we can choose either and construct a projection where the x-axis shows the difference of networks where $G < 0$ vs. networks where $G > 0$ (or likewise for K).

To define the x-axis of the plane in hENA, we regress each column of C:

$$\forall_j : C_j = \beta_j^0 + \beta_j^g G + \beta_j^k K + \beta_j^{gk} GK + \epsilon_j$$

For each column j, we have a coefficient β_j^g that is the *slope of the effect of* G on the grand mean of that column. If n is the number of columns, then $B^g = (\beta_1^g, \ldots, \beta_n^g)$ is the vector through C that represents the *direction* of the effect of G holding constant the other terms. Normalize B^g to find a unit vector:

$$U_x = B^g \;/\; ||B^g||$$

and project each of the networks in C onto U_x find their x-axis positions by $\dot{C}_x = C \times U_x$.

This in equivalent to the means rotation in ENA if $K = 0$.

Construct U_y in the same way, but from B^k. There is no guarantee that U_x and U_y are orthogonal, so to produce an orthogonal projection, compute:

$$\dot{U}_y = \frac{U_y - (U_y \cdot U_x)}{||U_y - (U_y \cdot U_x)||}$$

Then $\dot{U}_y$ is the unit vector with the smallest angle between itself and U_y while still being orthogonal to U_x.

Project each of the networks in C onto $\dot{U}_y$ to find their y-axis positions by $\dot{C}_y = C \times \dot{U}_y$.

Now the y-axis models the effect of K *independent* of the x-axis, which models G. There is no equivalent in current ENA tools for defining the y-axis this way.

3 Example

For example, we use data from the RescueShell Virtual Internship [2], one of the default datasets in rENA and the ENA webkit. Because of space constraints, we do not describe the virtual internship or data set in detail, other than to say that there are 6 codes and two grouping variables: Condition and GameHalf.

Figure 1 shows two mean networks constructed with hENA such that G is the variable Condition with values < 0 = *FirstGame*, > 0 = *SecondGame* and $K = 0$. That is, equivalent to a means rotation on the variable Condition in ENA. The squares on each plot represent the means for each condition. The ▼ on each plot is the mean of each condition during the first half of the game (variable GameHalf = *FirstHalf*); the

[2] In practice, G and K can be any mean-centered continuous variables, but they must not be colinear and for interpretable results they must be in theory uncorrelated.

▲ is the mean of the condition during the second half of the game (variable GameHalf = *SecondHalf*).

In the First Game (left, purple), students were less experienced and made more connections with **collaboration** (e.g. discussing who will work on what) and **technical constraints**. In the Second Game (right, orange), students were more experienced and made more connections with **design reasoning** (a key practice of design) and **performance parameters**.

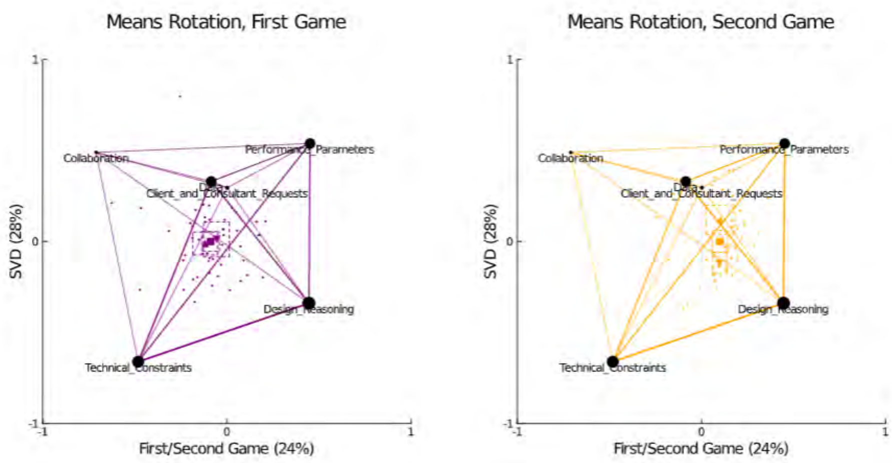

Fig. 1. Comparing First Game (left) and Second Game (right), with First Half and Second Half subgroup means shown with ▼ and ▲ respectively.

Figure 2 shows two plots that subtract the First Game network from the Second. The means rotation on the left summarizes the results of the two individual plots in Figure 1, where the x-axis shows the variable Condition and the y-axis shows the highest variance dimension of C that is orthogonal to the x-axis. This plot suggests that the less experienced students discussed the problem in the same way throughout the simulation: the means for each game half are more or less coincident with the overall mean for the group. The more advanced students discussed the problem differently, focusing more on **design reasoning** in the first half (▼) and **performance parameters** in the second(▲).

The plot on the right is an hENA plot such that G is the variable Condition and K is the variable GameHalf. The x-axis placement of the codes now models the impact of Condition *controlling for* GameHalf, and y-axis placement of nodes models the impact the impact of GameHalf *controlling for* Condition.

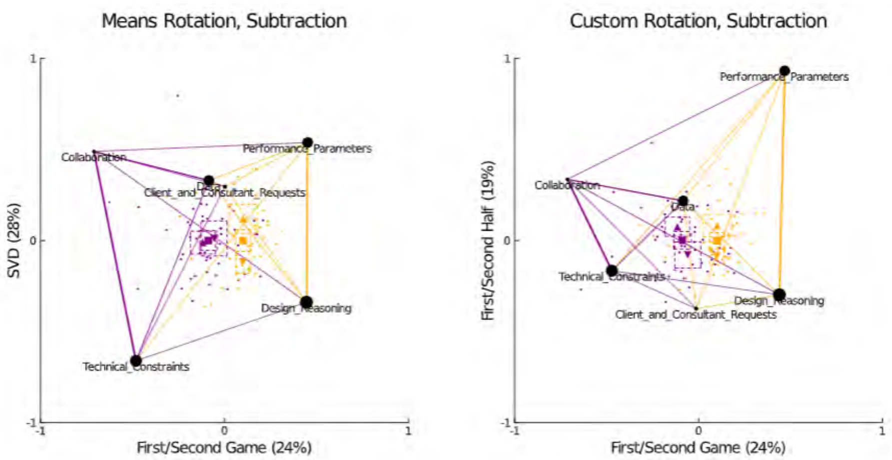

Fig. 2. Subtraction of First and Second Game, comparing standard ENA means rotation (left) and hENA (right) with variables on two axes

In this projection, all four subgroups are clearly separated, and we can now see that students in the First Game *did* talk about the problem differently. The change in y-axis positions of **performance parameters**, **client and consultant requests**, and **technical constraints** shows that students in *both* games made different connections in each half of the game.

4 Conclusion

hENA can thus provide more information about the data than an ENA means rotation by accounting for two grouping variables simultaneously. And because hENA uses a regression to perform the projection from C to $\dot{C}$, it also has the potential to account for multi-level nested structures and model the significance of continuous variables. We hope to report on those features in future work.

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A Systematic Review of Quantitative Ethnography Methods

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Abstract: Quantitative Ethnography (QE) is a novel discipline unifying quantitative and qualitative methodologies with various methods and tools. We aimed to conduct a systematic review of the proceedings from the 1st International Conference for Quantitative Ethnography in order to compare methodological decisions researchers made. Data was extracted with a standardized template and coded deductively by a team of researchers. Our findings show that although many QE terms and processes (e.g. concerning coding and segmentation) were employed, they were often not reported explicitly or defined. We encourage open communication about methodology for the benefit and progression of the QE community.

Keywords: Quantitative Ethnography · Epistemic Network Analysis ·Systematic Review · Methodology

1 Introduction

Quantitative Ethnography (QE) is a nascent field working to develop a unified quantitative and qualitative methodology. This study aims to investigate the decisions researchers working in QE have made concerning study design and operationalization, as well as various QE-specific tools and concepts. Our objective was to perform a systematic review of the proceedings from the 1st International Conference for Quantitative Ethnography (ICQE) [1], in order to elucidate some of the methodological decisions that were made in those works. This study is part of a larger systematic review of QE publications that aims to spur intra- and inter-disciplinary dialogue on issues of methodology and operationalization, while also facilitating Open Science principles and transparency.

2 Methods

All papers in the ICQE19 conference proceedings were included in the present study (n=32). A training set of four articles was used to inductively create a tentative code system based on the constructs relevant to our inquiry. Four dyads of researchers employed the preliminary codes to the training set, then refined code definitions and discussed code applications. Subsequently, a new version of the codes was created, five researchers deductively coded another test set, then met to finalize the codes and code book. Final coding was performed for 32 entities (mid-level codes) using a standardized extraction template. The extracted information was aggregated with the R package "metabefor". The extraction process was optimized for retaining as much fidelity as possible, which resulted in many extracted text strings. These required further processing, which was conducted separately for each entity and achieved through inductive coding (in case of categorical values) or thematic analysis (in case of longer text strings) performed by two autonomous raters who triangulated their findings and negotiated the final results. All of our scripts and data are openly available at this Gitlab repository: https://gitlab.com/q-e/icqe-2019-sysrev.

3 Results

Study design. The majority of studies were empirical (n=22), three were theoretical (no empirical data was collected), and seven papers expounded theoretical issues with empirical data obtained in a previous study. Most empirical research involved human participants, with sample sizes ranging from 10 to 944, and two case studies. Of the 22 empirical studies, the most common form of data collection was observation (n=5), archive (n=4), and semi-structured interview (n=2). The most common types of data were text (n=9), audio (n=5), and audio-video (n=2). Sixteen studies considered the individual participant as the source of data, six further studies also collected group-level data, and two studies worked with dyads.

Coding. Most researchers employed deductive coding (n=12) or a mix of deductive and inductive processes (n=10), while only three used inductive coding. The number of codes varied greatly: seventeen studies employed 1-10 codes, five studies used 10-20 codes, and three had 20+ codes. In the majority of studies coding was performed manually or by combining manual and automated coding (n=17); coding was fully automated in only two studies. Coding was performed mainly by human raters, most frequently two or three researchers working autonomously (n=16). The majority of coding was conducted by humans only (n=12) or humans and a computer (n=11). Of the twenty-nine studies this was applicable, just over half (n=17) of the publications reported calculating inter-rater reliability (IRR), whereas just under half (n=12) did not disclose this information.

Segmentation. Discourse segmentation was performed in twenty-five of the thirty-two studies; seventeen of these defined their smallest unit of segmentation (utterance) as a sentence or a turn-of-talk, another four defined it as "a line" of data. Twenty-one studies calculated code co-occurrence, based on a higher level of segmentation, the "stanza", which most researchers (n=9) modeled with a moving stanza window of a certain size (generally the length of 3-5 utterances). Aside from this definition, stanzas were predominantly not reported or determined with a "naturally" occurring type of segmentation, e.g. a lesson plan constituted a stanza.

Analysis. Twenty-one studies generated network models with Epistemic Network Analysis (ENA). Network units were defined as individual participants and/or groups of participants in the study. Other empirical studies (n=2) utilized solely nCoder to analyze data, while the rest of such studies employed a variety of other analytical methods, e.g. Process Mining, Quantitative Multimodal Interaction Analysis, and Non-negative Matrix Factorization.

Conceptualization. Several papers were focused on QE methodology, but empirical studies were most commonly conducted within the disciplines of learning science and health care (n=17 and 6, respectively). Authors frequently addressed questions of identity and collaboration, exploring issues in collaborative learning, decision-making, and problem-solving. Twenty-seven studies expounded what QE and/or ENA signified to the studies and why they employed this methodology. Researchers chiefly conceptualized ENA as a means of quantifying qualitative data, thus being able to perform statistical analyses on narratives and creating network models of the relationship among coded elements in the texts. ENA was used in many studies to analyze unique datasets (transcripts, scraped data, etc.), model trajectories (investigating changes in data points over time), and compare patterns of behaviors among participants. QE was often only discussed as a methodological framework from which ENA emerged; QE definitions were commonly vague or, alternatively, direct quotes from David Shaffer, author of the book Quantitative Ethnography [2]. QE was described as a method to find meaning in data (especially big data), quantify qualitative data, and reveal systematic patterns. QE, however, was further explored in discussions of how it was utilized in each study, namely: to improve existing research methods, conduct comparison studies, test topic modelling, etc.

Lack of reporting. From our codes related to study design, coding, and segmentation, many were not reported by authors in the examined works: in the instances where it would have been applicable, about ⅓ of the studies did not include the number of raters, type of employed segmentation, or their definition of utterance and stanza. Similarly, many other authors did not report the number of their low-level codes (n=7), their coding process (n=6), or the IRR (n=8).

4 Discussion and Conclusions

We reviewed papers published in the 2019 ICQE proceedings in order to elucidate methodological decisions authors made in the scrutinized publications. Most studies were empirical and employed ENA to analyze qualitative data collected from individual human participants. We observed a lack of reporting in several areas. Regarding QE methodology in particular, more explicit reporting on the following criteria would benefit future work:

Figure 1: Areas of Reporting Suggested for Quantitative Ethnographic Studies

Coding	
✓	Code system creation
✓	Number of codes
✓	Process of coding
✓	Inter-rater reliability

Segmentation	
✓	Definition of utterance
✓	Definition of stanza
✓	Process of segmentation

Analysis (ENA)	
✓	Reason for employing ENA
✓	Definition of unit
✓	Definition of conversation
✓	Conversation window size

Open communication about methodology would benefit the development of QE as a discipline. Firstly, as with any theoretical framework, the QE framework is informed and shaped by its specific operationalizations in various projects. Secondly, scientific rigor and the advancement of best practices is spurred by openly accessible data, procedures, and well-documented decisions. Thirdly, as QE evolves and expands, novel methods and tools will be developed, which are more effectively disseminated through open communication. Our present study, and our broader ongoing systematic review, is an Open Science initiative to facilitate methodological discourse in the QE community.

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Comparing Natural Language Processing Approaches to Scale Up the Automated Coding of Diaries in Single-case Learning Analytics

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Abstract. This poster describes ongoing research exploring the performance of different natural language processing feature extraction and machine learning techniques, in mimicking qualitative coding of unstructured diary data. While initial results show relatively low performance, several important issues are unearthed (such as the influence of code prevalence) for discussion with the quantitative ethnography community. Further work will seek to complete this systematic exploration of the state-of-the-art in automated labelling.

Keywords: Automated Coding, Qualitative Content Analysis, Natural Language Processing, Machine Learning, Learning Analytics.

1 Research Problem

Most research in the field of Quantitative Ethnography (QE) focuses on education settings where a cohort of learners interacts and undergoes somewhat comparable learning processes. However, there exist settings where such cohort-based analyses and meaningful comparisons among learners cannot really be made (from doctoral education to lifelong learning).

Qualitative, single-case studies (including those using ethnographic methods) have been a natural way to investigate and understand the specificity of such single-learner processes, and the networks of meanings that can be used to interpret them, both from the learner's own perspective and in light of different theoretical frameworks. However, it is currently impossible to scale this kind of approach up to support every learner: we cannot possibly send an ethnographer after every learner to gather qualitative data for long periods of time, and continuously analyze it to provide the learner (and the research community) with insights about their learning process.

Taking advantage of recent advances in computation and in means for data gathering, we have proposed an approach to help learners in reflecting and understanding their own learning by gathering and analyzing quantitative and qualitative data over long periods of time. We have labelled this approach 'single-case learning analytics' (SCLA) [1]. Yet, this novel approach still relies on the qualitative analysis of unstructured data (e.g., learner diaries), which requires, in turn, considerable amounts of human effort to perform qualitative coding tasks. Hence, scaling up this

SCLA approach to make it practically relevant will require *automated coding* capabilities within such systems.

Within the QE community, the problem of automated coding is being tackled mostly through researcher-driven rules (e.g., via keywords or regular expressions) defined iteratively until an acceptable level of inter-rater reliability is achieved (e.g., Cohen's kappa > 0.65). This is, in fact, the approach followed by the widely-used nCoder system and related software packages (http://www.n-coder.org/).

With the advent of deep neural networks and other recent computational advances, alternative approaches that use natural language processing (NLP) to mimic human-labelled content are starting to appear. For instance, several efforts have been made in comparing different algorithms and feature extraction techniques to automatically classify questions according to Bloom's taxonomy of learning [2]. Closer to the QE field, researchers have used topic modelling to automatically code a large corpus of chat data, using it as a basis for epistemic network analyses [3]. Yet, it is still unclear whether these computationally-heavy automated coding approaches can perform reliably in the face of relatively small and highly heterogeneous datasets that SCLA would face in order to support non-cohort educational settings. This poster summarizes our general approach and first steps in assessing this question, through a case study using a dataset in single-learner, informal, lifelong socio-emotional learning (SEL).

2 Methodology

The dataset to be automatically coded was gathered during a case study aiming to understand in-depth aspects of self-directed socio-emotional learning (SEL) of a knowledge worker (a researcher). The main question of inquiry of the researchers and the learner himself, was *"What makes up a good day at my work?"* [1]. As part of the aforementioned SCLA approach, during 166 workdays both quantitative indicators and qualitative (open-ended, unstructured) diary entries were gathered. In total, the diary entries comprised 728 sentences. These diary entries were then coded manually, at the sentence level, using two different coding schemes: a) a very simple scheme labelling whether the sentence mentions progress or setbacks (based on prior work on worker engagement and satisfaction by Amabile and colleagues [4]); and b) a more complex, bottom-up open coding (made up of 62 codes), targeting contextual influences into the satisfaction (a well-known factor to take into account in SEL [5]).

Using this coded dataset as a base, our main research question is: *"How well can different NLP and machine learning (ML) algorithms mimic this human coding?"*. To answer this question, we are conducting a two-stage ML modelling study:

1. a wide-spectrum exploration of different NLP feature extraction approaches (bag-of-words, TF-IDF, word/sentence embeddings, and linguistic features) and ML algorithms (from classic models like Naive Bayes to deep neural networks), to understand the overall landscape of options and their performance; and
2. a deep-dive into optimizing the performance of selected feature extraction approaches and ML models (shown as most promising in stage #1), to understand the relative value of optimizing model parameters vs. using default ones (a considerable time investment in many ML projects).

In all cases, the different feature/model combinations were compared through stratified 5-fold cross-validation, repeated 5 times, to get an idea of the distribution of expected performances (in terms of Cohen's kappa) when trying to code a new diary entry that it has never seen before. This evaluation was performed for each of the 64 codes in the two coding schemes (which have varying levels of prevalence/rarity).

3 Initial Results

In this section, we report the initial results of the ongoing stage #1 of our analysis. At the conference, results from both stages will be reported. As of this writing, the wide-spectrum exploration of various feature extraction approaches (bag-of-words, TF-IDF bag-of-words, and linguistic features), with different kinds of classic ML algorithms (Naive Bayes, Support Vector Classifiers, Logistic Regression, Random Forests and Gaussian Processes), has obtained underwhelming results.

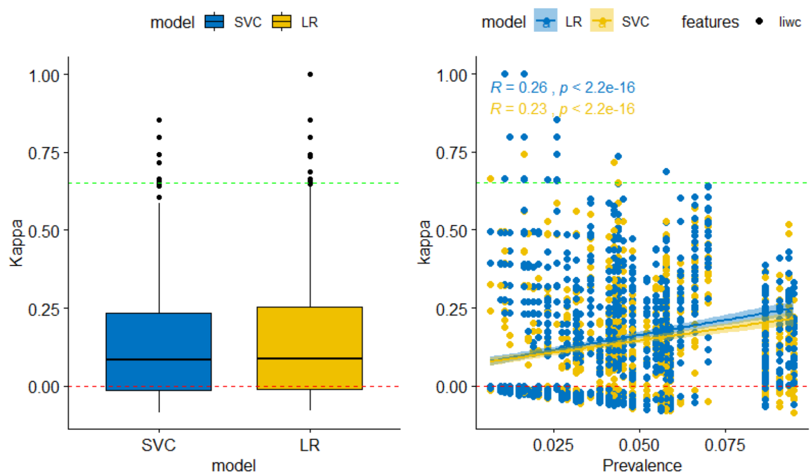

Fig. 1. Distribution of inter-rater reliability (Cohen's kappa) between the human coder and selected feature extraction and ML models, from our wide-spectrum exploration (left). Variation of the models' reliability with each code's prevalence in the dataset (right).

In general, we can see that the performance in terms of kappas is quite far from the desired values of 0.65 and above (see Fig. 1, left). On average, the best-performing feature extraction technique seems to be the linguistic features (as extracted using the LIWC software package [6]). In terms of ML algorithms, so far Logistic Regression and Support Vector Classifiers seem to be performing the best using the aforementioned linguistic features, with median kappas across all codes of 0.087 and 0.085, respectively. We can also observe that the prevalence of a code (i.e., how rare or common it is in the dataset) influences the models' performance, which degrades as codes become rarer (see Fig. 1, right).

4 Discussion and Expected Feedback

While initial results from simpler feature extraction and machine learning techniques are underwhelming, this ongoing wide-spectrum exploration still has not exploited some of the most advanced NLP/ML techniques available, such as word/sentence embeddings or recurrent neural networks. Yet, this initial exploration has already unearthed interesting issues: the kinds of features that seem most helpful to train automatic coders (i.e., linguistic ones), or the influence of code prevalence on the effectiveness of these techniques. During the conference, we hope to spark discussions and feedback from the QE community, around:

- Problems that are inherent in the automated coding of (relatively small) ethnographic datasets, such as the low prevalence of codes, and what techniques can be used to ameliorate these problems.
- Comparisons (and complementarities) between NLP-based and rule-based, researcher-driven approaches to automated coding (e.g., as shown in nCoder+ [7]), especially in terms of optimizing the amount of human effort.
- The need for explainability (vs. black-box modelling) in the feature extraction and ML models we use for automated coding, in case there exists a tradeoff between explainability and performance (cf. the discussion in [8]).
- Novel ways of including learners themselves (not only researchers) in the interpretive/coding loop. This is crucial given SCLA's overarching aim to directly support individual learners using qualitative/ENA analyses, and could be achieved through semi-supervised or reinforcement ML techniques, but also through finding coding schemes that are both theoretically sound and meaningful and actionable for the learner.

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U.S. Media Coverage During COVID-19: An Epistemic Network Analysis of Bias, Topic, and Trajectory

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Abstract. Quantitative ethnography (QE) is an emerging methodology for novel examination of data and discourse through a combined qualitative and quantitative lens. QE has been utilized in many fields, from surgery to education, but has yet to provide much commentary on either political bias or news media discourse. This study analyzes the bias and trajectory of news media coverage during the early COVID-19 pandemic in the United States. Titles of articles mentioning the virus from three distinct weeks were sampled, hand-coded by two raters, and modelled using Epistemic Network Analysis (ENA) along with metadata about their publication's bias. Our findings showed 1) a statistically significant difference between right- and left-leaning news media topic connections and 2) a common trajectory of topic emphasis followed by right, left, and center media.

Keywords: Quantitative ethnography, News media, Political bias, COVID-19, Epistemic Network Analysis (ENA)

1 Introduction

Quantitative Ethnography (QE) is an emerging methodology that integrates quantitative and qualitative methods to create meaningful and novel discourse analyses. QE has been used in a number of disciplines, from analyzing surgical procedures to assessing K-12 student learning interactions [1]. However, as of yet there has been little quantitative ethnographic analysis of large-scale political or journalistic discourse. Using Epistemic Network Analysis (ENA), a dynamic network modelling tool that maps relationships between codes in discourse data, we provide an analysis of U.S. media coverage of COVID-19-related news during February and March 2020.

U.S. news media bias has been rising for years; according to a 2018 poll, 45% of Americans say they see a "great deal" of political bias in news coverage, up from 25% in 1989 [2]. Our goal is to understand how these biases manifested themselves and interacted with other matters of global and national importance during early U.S. COVID-19 spread. We used ENA to answer the following: how did the most frequently related subjects of reporting differ between Right and Left media, and how did those relationships and trajectories evolve as pandemic reporting progressed?

2 Methods and Design

The data in this study was sourced from an exploratory project performed as part of the International Society for Quantitative Ethnography's April 2020 QE-COVID Data Challenge. Data was downloaded from a Webhose dataset featuring "English news articles that mention 'corona virus' or 'coronavirus' or 'covid'" [3]. The dataset was then merged with AllSides.com's Media Bias Ratings [4], preserving only articles from publications rated by AllSides. Ratings of Left/Lean Left and Right/Lean Right were condensed into simply Left and Right. We sampled three dates of epidemiological significance: Week 1, February 6 (first U.S. death); Week 2, March 11 (U.S. surpasses 1,000 cases); and Week 3, March 26 (U.S. has the most cases globally). Using R's **sample_n** function, we sampled 1,000 articles per event from a two-day window before and after each of the three dates.

We integrated the results of a grounded analysis with Latent Dirichlet Allocation (LDA) topic modeling to produce five codes (see Table 1). Each article title represents one line of data; lines were hand-coded by two independent human raters for each of the codes, then reconciled via social moderation [5] to achieve perfect agreement (kappa coefficient=1.00, Shaffer's rho ≤ 0.00).

Table 1. Codebook.

Code Name	Definition
Elections	Discourse related to election cycles in the U.S., including local, state, and (largely) national elections, campaigns, and candidates.
Economy	Discourse related to the global or domestic macroeconomy.
Domestic Tracking	Discourse surrounding the tracking and spread of COVID-19 to and within the U.S. This includes reporting on disease statistics, severity indicators, and transfer mechanisms (planes, ships, etc).
Global Tracking	Discourse surrounding the global spread and tracking of COVID-19. This includes reporting on disease statistics, severity indicators, and transfer mechanisms (planes, ships, etc).
Cancellations	Discourse related to the cancellation, closure, and postponement (but not reopening) of commercial and recreational spaces and events.

The coded headlines were then entered into Epistemic Network Analysis (ENA) for analysis. Units used were bias > week > publication, with stanza size being a whole conversation consisting of week > publication. We then compared Right and Left aggregate networks and the week-by-week trajectories.

3 Results

A two-sample t test assuming unequal variance from the resulting ENA model showed a statistically significant difference at the alpha=0.05 level between Right (mean=0.07, SD=0.28, N=58) and Left (mean=-0.04, SD=0.32, N=98; t(133.40)=2.29, p=0.02, Cohen's d=0.37) along the X-axis. The comparison plot (see left side of Fig. 1) shows that the driver of this statistically significant difference between Right and Left media outlets was that, relative to the Left, the Right media's strongest connections were between CANCELLATIONS and DOMESTIC TRACKING. In contrast, relative to the Right, the strongest connections in Left media were between ELECTIONS and ECONOMY and ECONOMY and GLOBAL TRACKING.

The next result was based on a trajectory analysis between weeks for both Right and Left. As we can see on the right-hand side of Fig. 1, both Right and Left means for Weeks 1-3 follow a similar path. Looking at individual plots for Right and Left, in Week 1 we found significant connections between ECONOMY and GLOBAL TRACKING for both sides. In Week 2, although specific connections differ, CANCELLATIONS is the most frequently related-to code for both, causing a downward and rightward shift from Week 1. In Week 3, the shift downward and rightward was driven by both sides displaying more connections with ECONOMY, but still relating strongly to CANCELLATIONS. Although not included in the figure, we also saw these patterns in Center media, indicating an overarching phenomenon.

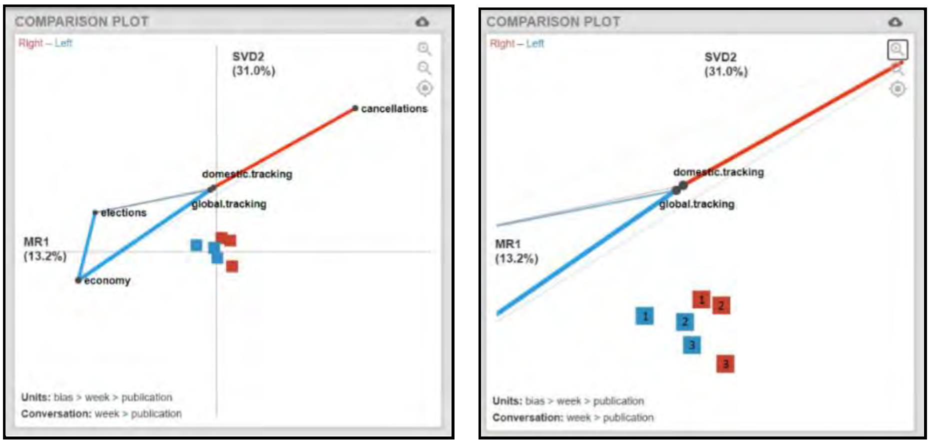

Figure 1. The comparison plot (left) shows the difference network for Right media (red) and Left media (blue) plotted together. In the week means (right) for Right and Left, the pattern forms an "elbow" shape, showing coordinating trajectory movement over time.

4 Discussion

Our analyses found differences between the codes most frequently connected between Right and Left media outlets; however, despite having unique biases, the Right and Left's reporting trends across weeks appear to follow parallel paths.

According to polling, conservative Americans have in recent years ranked the economy as one of their most important political issues, while liberals consistently rate it much lower in their list of priorities [6]. Therefore, we initially expected the Right media to have stronger and more frequent connections to ECONOMY than the Left. However, the ENA evidence shows strong Right discourse around CANCELLATIONS, and less about ECONOMY. With 81% of Democrats compared to a lesser 61% of Republicans supporting the closing of all non-essential business [7], the stronger connection frequency of CANCELLATIONS (a code mainly about individual business-related closures) as compared to ECONOMY (a code describing more macro-level economic events) might indicate that the Right's concern about commercial activity is actually more in regard to individual rights to market access. Because there is no code that makes the distinction between micro- and macro-economic concerns, CANCELLATIONS may be effectively acting as a proxy for microeconomic discussion in Right media. Right-media stories with headlines like "Alex Villanueva, Los Angeles County sheriff: Gun shops not essential, must close" (Washington Times) demonstrate the Right media's alarm about limiting access to goods, services, and activities they believe Americans have a fundamental right to purchase or partake in.

The strong connections between ELECTIONS and ECONOMY in the Left's discourse could be interpreted as reporting bias against certain partisan candidates in the November 2020 election. As Republicans currently hold the presidency and the Senate, the economic expansion that has occurred since 2016 has been a major re-election campaign focus for Republicans, with 84% of voters saying the economy was "very" or "extremely" important, more than any other issue [8]. For this reason, Left media could be focusing on the macroeconomic fallout of the pandemic to undercut the current Republican administration's economic track record (e.g., "The Dow has lost more than 18 percent of its value since Trump boasted of 'highest stock market in history'" [Raw Story]) and promote liberal candidates, creating the ECONOMY-ELECTIONS connection.

We also recognize that these results are limited insofar as our study utilized only a subsample of headline-only article data, with the goal being an initial inquiry into use of ENA for political media discourse analysis. In further study for thicker description, we would recommend a deeper look into article contents with a larger sample.

Acknowledgements. This study is based on an exploratory project by J. Seo, S. Choi, P. Tedoff, D. Kim, A. Fogel, S. Buckingham Shum, and Z. Cai as part of the QE-COVID Data Challenge. Their work provided much of the coding structure, data collection, and framework that was essential to this study. 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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Messy ENA? Considering Approaches for Implementing Relational Modes in Epistemic Network Analysis

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Abstract. In this project, we present a new approach to ENA that focuses on *how* codes are connected and introduce various methodological techniques to applying this orientation through an analysis of qualitative data from the 2006 Latino National Survey Focus Groups. When feasible, we conclude that these approaches can yield substantial quantitative and visual advantages over a typical ENA model.

1 Introduction

Qualitative data has grown rapidly in scale and availability in recent years. Popularized recently, an essential technique to analyze such large qualitative data has been Epistemic Network Analysis (ENA), which models the symbolic connections being made, and effectively reduces and visualizes the data [1]. Our novel approach to ENA is built on the idea that while ENA elegantly captures *which* concepts are tied together within a qualitative dataset, it generally has limitations in quantifying and visualizing *how* concepts are tied together. This idea is essentially Relational Analysis, which is analysis that focuses on the relationships between the concepts present in text [2]. In application, we introduce the *Relational Sub-Network*, a sub-unit blocking variable where we implement *Relational Modes,* discrete/distinguishable forms in which a pair of codes are connected, into ENA. We term our orientation and approach Messy Epistemic Network Analysis.

This project's data comes from the 2006 Latino National Survey Focus Groups, a publicly available qualitative dataset. [3] This data consists of 13 focus group transcripts totaling more than 130 participants. Metadata on gender was already included within the dataset. We generated potential codes by considering common themes of the dataset identified by the authors in the documentation and discussing our observations of common themes and topics. Automated classifiers to code the data were then verified and applied via nCoder. We utilized the Syuzhet R package in order to perform the Sentiment Analysis. While there are multiple Sentiment Analysis forms, we utilized "NRC" sentiment analysis, which detects the presence and level of ten emotions/sentiments.

1.1 Model 1 - Ordinary Model

In the Ordinary Model, we applied a set of 10 codes to the data via automated classifiers and the NRC sentiment analysis detected the Emotion/Sentiment present in each segment and applied a "code" for each segment. Utilizing rENA, we then generated an ENA model, comparing Males' and Females' networks, where each unit was a unique participant in the focus groups. For the most part, this model (which is not pictured) is difficult to understand. At 20 codes, there is far more than should generally be in an ENA model. Most significant, we can only logically interpret single connections among codes and relational attributes, and there is no way from this model to understand how sentiment connects two codes directly.

1.2 Model 2 - Convenient Model

In the Convenient Model, we applied the same set of 10 codes to the data via automated classifiers. NRC sentiment analysis detected sentiments in each segment and using the earlier described technique, we identified a single "dominant" sentiment. Each text segment was subsequently re-coded as belonging to a unique combination of "speaker" and "emotion/sentiment". We subsequently generate the ENA models, in rENA with the "speaker"-"emotion" codes being the units. This approach allows us to generally compare both genders and the genders-specific emotional categories, or "relational sub-networks" as we call them.

1.3 Model 3 - Advanced Single Model

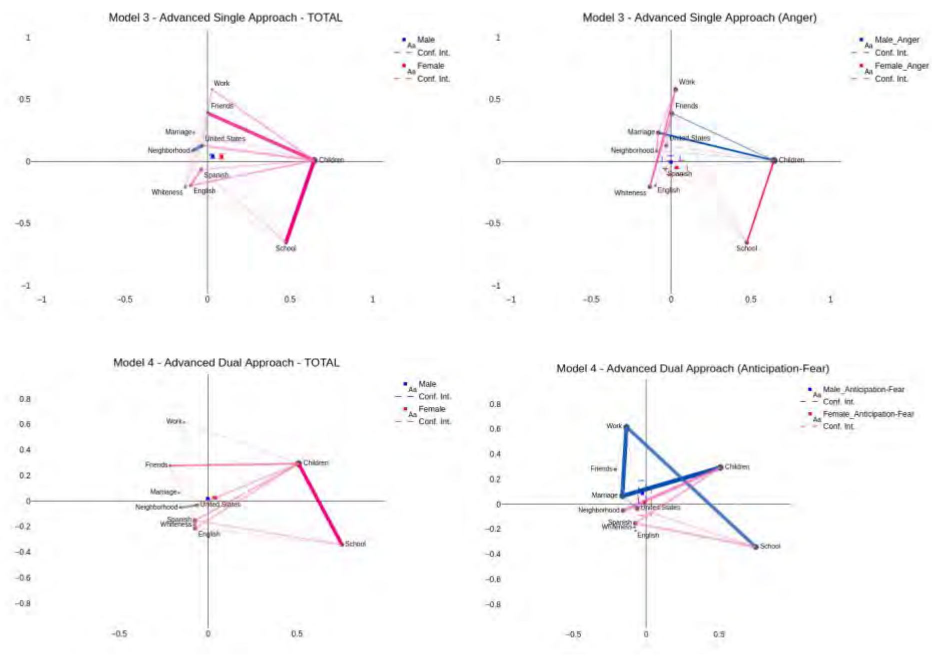
In the Advanced Single Model, we applied the same set of 10 codes to the data via automated classifiers. In this approach, NRC sentiment analysis was applied to a series of subsequent segments that contained a specific and unique co-occurrence of codes. Due to this unique approach, we had to generate a new dataset, preserving all other data, but creating a unique stanza for every co-occurrence of codes within each dataset, and then coding all segments within each unique stanza with the sentiment detected. Each segment's unit is thus subsequently labeled as a combination of the original speaker's name and the sentiment of the stanza the segment is in. The Anger sub-network comparison in our Figure demonstrates how sub-networks can show nuanced relationships between codes, with men making much stronger connections between *Marriage* and *Children* and women making much stronger connections between *Work* and *Whiteness.* Referring back directly to the text finds specific examples to support the relationship. For example, a female subject says: *I work in an office where the majority of the employees are whites...i know that a lot of discrimination its (is) going on here."*. We see the female subject is tying *Work* and *Whiteness* with anger due to her observation of racial discrimination at work from white co-workers.

1.4 Model 4 - Advanced Dual Model

In the Advanced Dual approach, as in the Convenient Model, every segment within the dataset was coded as having a single overlying sentiment. Similar to the Advanced Single approach, a new dataset was generated from the first, such that every co-occurrence of codes had a unique stanza of minimal size. Distinct, however, we coded all segments in each stanza not as having a single sentiment, but as having an unordered combination of two sentiments, one sentiment being the dominant sentiment in the first segment in the stanza, and the other being the dominant sentiment in the last segment in the stanza. With sub-networks being of a unique sentiment combination, we now have over 50 different sub-networks to consider, substantially refining the nuances we can examine. Figure Four of the Anticipatory-Fear sub-network depicts the differences in connections men and women make when talking about a code in an anticipatory way and connecting it to a code that is being discussed fearfully, or vice versa.

2 Model Comparison and Discussion

As discussed, our three latter approaches to implementing Relational Modes into ENA offer substantially more in-depth models than an ordinary model might. The convenient approach can be easily implemented and can descriptively visualize and quantify what codes are connected across a variety of Relational Modes. The convenient approach is only flawed relative to the Advanced Single approach in having a presumably lower degree of reliability. Finally, the Advanced Double approach is a unique approach that can qualify the co-occurrence of codes with the co-occurrence of Relational Modes. This level of modeling is highly-detailed, and achieving statistical significance for sub-networks may be difficult without a very large amount of qualitative data, as well as may not be appropriate for all types of data and all types of Relational Modes. In this paper, we have outlined an orientation and several methodological approaches for incorporating the nature of *how* codes are connected into Epistemic Network Analysis, which we call Messy ENA. While not feasible for all datasets, these approaches can prove advantageous when applicable, offering a more nuanced analysis of qualitative data, providing more specific quantitative warrants and visualizations.



Figures. Fig. 1 is top left, Fig.2 is top right, Fig. 3 is bottom left and Fig. 4 is bottom right

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Uncovering Latent Topics of Blind People in Computer Science: Structural Topic Modeling for an Email Corpus

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Abstract. The purpose of this work is twofold: (1) to discover community knowledge of blind people in a computer science listserv; (2) to contribute to methodological discussion on topic modeling by sharing our application as an example. Discussions include how a large-corpus email data (n = 13,236) of a computer science listserv for the blind can be estimated with optimal K values.

Keywords: Structural topic modeling, STEM learning, Blind.

1 Background

Most scholars now believe that more inclusive STEM (Science, Technology, Engineering, and Mathematics) materials and scaffolding learning designs are imperative for students with disabilities to fully engage with its content [1]. While individuals with disabilities still lack accessible STEM curricula, blind students, in particular, experience extra challenges due to STEM field's vision-dominant nature [1]. Despite these critical lags behind their sighted counterparts, scant research has been devoted to investigating "How Blind People Learn STEM" in scientific ways with a hasty conclusion that a costly retrofitted change must be required for their special needs.

This research will contribute to a comprehensive understanding of how blind people learn STEM in general. Additionally, it will also report what challenges and solutions have been discussed among blind people to engage them in STEM education specifically through reproducible data mining and natural language processing on a large-scale email corpus produced by blind individuals.

2 Conceptual Framework

This study views learning as the development of an "epistemic frame" [2], defined as "a *pattern* of associations among *knowledge*, skills, habits of mind, and other cognitive elements that characterizes *communities of practice*" (p. 11, emphasis added). From this perspective, STEM-oriented email archives of a group of blind people can provide researchers with countless value in deeply understanding the unique patterns of their learning, shared cultures, and networked knowledge relationships between the members.

3 Methods

The overall research procedure follows the five steps of "Knowledge discovery in databases (KDD)" [3]: (1) data selection; (2) data cleaning; (3) data transformation; (4) data mining; and (5) results evaluation and interpretation. This work, in particular, is focused on the data mining phase using a large-scale textual email corpus.

The target community of this quantitative ethnography is the National Federation of the Blind (NFB), which is one of the world's largest blind communities. More specifically, the data demonstrated in this study has been collected from the public NFB Computer Science (NFB-CS) listserv [4] that contains members' communication between January 2009 and December 2019. A total of 13,236 messages have been obtained, and 538 unique email addresses and members' names have been securely pseudonymized using one of the 64-bit salt-hashing algorithms.

First, we converted plain-text emails into a tidy data frame of one-message-per-row structure with 11 variables via the first author's developed R package "mboxr" [5]. Second, text preprocessing, such as stop-word removal and word-tokenization were conducted for message `subject` and `content` variables. Third, topics were estimated using structural topic modeling (STM) algorithm [6] with two prevalence covariates (year; the number of participants per each message). The optimal number of topics (K) was chosen based on two strategies: (1) the diagnostic analysis on held-out likelihood and residuals; and (2) relationship analysis between semantic coherence and exclusivity.

4 Results

To identify the best number of topics, we trained and compared seven topic models with different K values (20, 40, 50, 60, 70, 80, 100). We then visualized two diagnostic plots for evaluation. Figure 1 shows model diagnostics by number of topics. The held-out likelihood is highest between 20 and 50, and the residuals are lowest around 40 (16.09). Exclusivity and semantic coherence metrics were plotted as a scatterplot (Figure 2) to explore the best optimal K value—models with fewer topics have higher semantic coherence than more topics, but lower exclusivity. Given the tradeoff, it is good practice to choose balanced K value. Drawing upon these holistic diagnostics, we determined 40 as the optimal number of topics for the given corpus and visualized top 20 topics out of 40 by prevalence in the corpus (Figure 3). In the figure, γ matrix indicates the probabilities that each document is generated from each topic; each topic is a mixture of probabilistically contributing words.

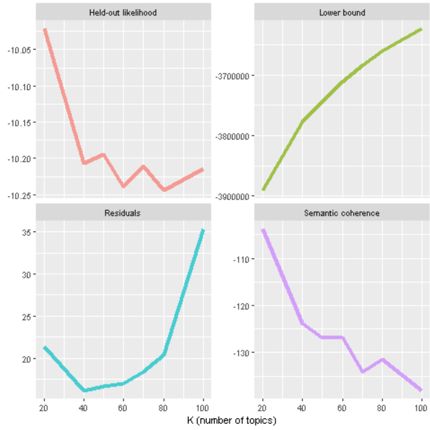

Figure 1. Model diagnostics by number of topics.

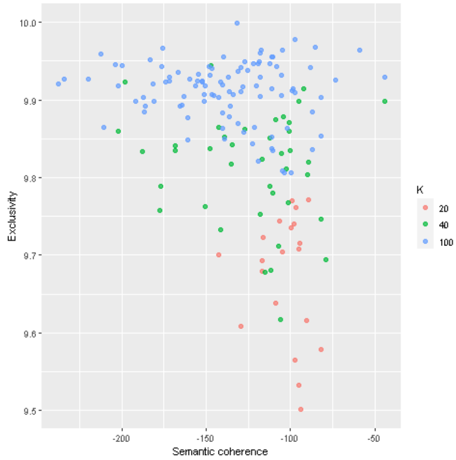

Figure 2. Comparing exclusivity and semantic coherence.

Figure 3. Top 20 topics by prevalence in the corpus with the top 7 words that contribute to each topic.

5 Discussion Points

We can see that most of the topics are focused on how to use Windows (topics 24; 39) and Microsoft Office suite (topics 19; 35; 32; 4) with screen-reading software (e.g., JAWS and NVDA). Topic 21 shows that blind people rely heavily on keyboard shortcuts when using computers. This is because mouse control is challenging for blind people to interact with GUI interfaces. While general computer usage on Windows operating system seems to be the most active listserv topics, there are other topics concerning different platforms. For example, topic 2 illustrates blind people are interested in using iOS and mobile apps with its built-in screen reader called VoiceOver. However, there is no significant topic on Android. This suggests that Apple's iOS accessibility is more consumed by blind people than any other mobile platforms.

More advanced listserv discussions can also be found. Java programming using eclipse IDE (topic 38) and Linux system engineering (topics 22; 13) and computer device management (topic 12; 8) illustrate that blind people can achieve high-level computational work as long as the related environments are configured to their assistive technologies (e.g., refreshable Braille display; screen readers).

Although this study has uncovered some basic understanding of the target email corpus, there are some limitations that we plan to address in our future research. First, we have found some topics that need to be filtered out. Topic 33 is a set of texts for the listserv email header and topic 6 is for email footer. Future work is required to deal with such general purpose words for email corpus systematically. Second, we have not yet investigated how these topics change over time. Since we have trained this model with the two prevalence covariates (year and num_discussants), we will illustrate how such two moderators effected the estimated topics for the next study.

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Tracing and Visualizing Clinical Judgment in Virtual Reality Simulations for Nursing Education

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Abstract. Quantitative Ethnography (QE) offers a novel approach for tracing and visualizing undergraduate nursing students' *clinical judgment* skills in virtual reality (VR) simulations. Clinical judgment is a highly valued skill set to cultivate because nurses are responsible for making a significant portion of decisions in health care. The National Council of State Boards of Nursing (NCSBN) operationalizes clinical judgment as nurses' ability to recognize cues about a clinical situation, generate and weigh hypotheses, take action and evaluate outcomes for the purpose of arriving at a satisfactory clinical outcome. High-fidelity simulation-based experiences have afforded rich contextual learning environments for fostering clinical judgment in nursing students. In this poster, QE approaches will be used to model the structure of connections in discourse data and visualize patterns of clinical judgment enacted during the course of the VR simulation activities (pre-briefing, the simulation itself, and debriefing). This formative work is positioned to extend QE techniques to nursing education.

Keywords: Nursing Education, Clinical Judgment, Virtual Reality Simulations, Epistemic Network Analysis

1 Background and Research Goals

Clinical judgment has been linked directly to nearly 50% of tasks performed by entry-level nurses, followed by problem solving and critical thinking. However, novice nurses struggle to make effective clinical decisions [1]. The National Council of State Boards of Nursing (NCSBN) created the clinical judgment measurement model [2] to help nursing education closely align with how nurse practice. The NCJMM can be broken down to capture how nurses arrive at sound clinical decisions. Figure 1 illustrates the "layers" of the NCJMM, with layer 3 operationalizing the cognitive processes underlying clinical judgment; i.e., recognizing cues about a clinical situation, generating and weighing hypotheses, taking action and evaluating outcomes for the purpose of arriving at a satisfactory clinical outcome. Layer 4 includes environmental and individual factors impacting clinical judgment. The NCJMM is valuable for guiding measurement and helping derive valid inferences around the nursing clinical judgment and decision-making ability of prospective entry-level nurses.

There has been an upward momentum in the use of simulations as an alternative to clinical experiences because simulations afford students a safe environment to apply theory to practice and to build competence over time [3]. "Simulations are activities that mimic the reality of a clinical environment and are designed to demonstrate procedures, decision-making and critical thinking through techniques such as role-playing and the use of devices such as interactive videos or mannequins" [4]. A review of the literature found significant increases in clinical judgment in nursing students after multiple exposures to high-fidelity simulation-based experiences [5]. Virtual reality (VR) simulations have the potential to enhance clinical nursing education [6]. They offer immersive experiences in a three-dimensional environment wherein the user can participate in a scenario with a headset that generates images and sounds similar to a real or imaginary world, communicate with team members, perform relevant actions using controllers, and receive haptic feedback. As the use of simulations increases and modalities through which they are delivered get more complex, the ability to synthesize and examine multimodal data becomes more critical in order to make sense of students' performance in clinical scenarios [7,8]. Learning analytics have offered promise when employed in a healthcare simulation classroom aiming to uncover small group learning, collaboration and enactment processes [9]. Its application to track clinical judgment in nursing education is underexplored.

The goal of this poster is to trace and visualize patterns of clinical judgment in nursing students as a result of their engagement in VR simulation activities. This proposal is situated in a larger pilot study designed to test the efficacy, usability, and viability of a VR simulation system for nursing education. The author will employ a quantitative ethnographic approach [10] which bridges qualitative and quantitative analyses to make statistical warrants about thick descriptions. Specifically, ENA will model the structure of connections in data and visualize patterns of clinical judgment enacted during the course of the VR simulation activities (pre-briefing, the simulation itself, and de-briefing).

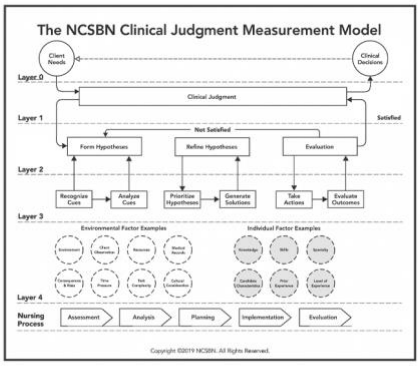

Fig. 1. The NCSBN Clinical Judgment Measurement Model (NCJMM)

2 Methods

2.1 Participants and Settings

Participants will include a group of 1-2 faculty members from undergraduate nursing programs who are interested in augmenting clinical experiences for their students using novel modalities for simulations such as virtual reality. The group will also include 2-

4 students. The faculty will be expected to facilitate the scenario using a moderator tool developed as part of the VR simulation system, and to make observations about students' progress in meeting the objectives of the scenario. The students will assume the roles of primary nurse practitioners in the VR environment and participant observers. All participants will be assigned preparatory activities prior to the simulation. These would include reading assignments relevant to the simulation scenario, instructions to set up the hardware (i.e. Oculus Enterprise headset and controllers), software (i.e. moderator tool), and the play space. Given the uncertainty of college re-openings due to the COVID-19 pandemic, the pilot study may run online only, in a hybrid format, or onsite. Nonetheless, the procedure for data collection will remain standard across the data collection sites. This is possible because the VR simulation system for nursing education is designed for participants to collaborate in a virtual space while being present in physically remote locations.

2.2 Data Collection

Data will be obtained from the application of an advanced medical-surgical simulation scenario in VR. The goal of this scenario is to provide students with the opportunity to assess, prioritize, and manage care for a patient experiencing an anaphylactic reaction to an IV antibiotic. The performance objectives for the scenario in relation to clinical judgment are for students to recognize abnormal findings (e.g. erythema and pruritus, decreased blood pressure), prioritizing and implementing appropriate interventions (e.g. stopping IV antibiotic, applying oxygen via face mask, administering epinephrine subcutaneously), and integrating evidence obtained to make sound clinical decisions for the well-being of the patient. For this poster, discourse data obtained during the simulation will be analyzed; i.e., transcript from the pre-briefing, role-play in the simulation scenario, and de-briefing.

2.3 Data Analysis

Once collected, student data will be inductively and deductively coded by two raters to each line of data [11]. Each line will be coded for the occurrence (1) or non-occurrence (0) of the skills that are essential to clinical judgment (i.e. layers 3; See Table 1); thus, quantifying qualitative data, and preparing the data for Epistemic Network Analysis (ENA). The association structure between the changes in students' ability to demonstrate clinical judgment will be modeled based on their co-occurrence in the specific implementation of VR simulation, by the three data points as pre-briefing, during-simulation and debriefing. As such, ENA will offer a unique way to recognize the patterns of clinical judgment at both the group and individual levels as defined by the NCJMM as a result of the VR simulation. Mann-Whitney U tests will ascertain whether differences in individual and group trajectories over time are statistically significant. The researcher will refer back to interactions and activities coded in the data to close the interpretive loop and thus fully understand the phenomenon mirrored in the model for each student and the group at large. This last step will enable the researcher to highlight the dominant issue for this poster- making nursing students' clinical judgment visible- an endeavor that is valuable for both nursing educators and students.

3 Anticipated Results, Limitations, and Implications

This poster will consist of epistemic networks that track shifts in clinical judgment for undergraduate nursing students in a VR simulation, paired with qualitative case studies to contextualize individual trajectories. ENA has been employed to assess communication patterns in a high-performing primary care team [12]. Scholars have also used multimodal data in healthcare simulation studies [9]. The author is keen to present this formative work and received feedback in order to extend QE to nursing education.

Table 1. Definition of NCJMM Layer 3 Codes

NCJMM Layer 3 Construct	Definition
Recognizing Cues	Filtering Information
Analyzing Cues	Organizing and connecting/clustering information to patient needs
Prioritizing Hypothesis	Evaluating and ranking assumptions about patient problems
Generating Solutions	Identifying relevant interventions
Taking Actions	Putting solutions of highest priority to effect
Evaluating Outcomes	Measure observed outcomes and compare them with expected outcomes

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Tracking Identity Exploration in Maker-based Learning: A Quantitative Ethnographic Approach

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Abstract. This paper reports findings from Invent with Environment, a maker-based after-school program which sought to develop and test maker courses for supporting high school and middle school students' identity exploration in environmental science. Identity exploration trajectories are illustrated for two participating in-service environmental educators who were seeking to integrate maker-based activities into their instruction. Data collection occurred across 14 weeks and three sessions which included a professional development and two course iterations. The work concludes with implications for supporting educators' cognitive skills and motivational attributes that can inform the use of making for a nuanced form of learning such as role-specific identity exploration.

Keywords: Identity Exploration, Epistemic Network Analysis, Projective Reflection, Learning By Making, Maker Education.

1 Introduction

Learning by making (maker-based learning, maker-centered learning) has been lauded by educational researchers for its ability to facilitate new ways of understanding concepts, supporting identities and dispositions, and triggering future trajectories in academic domains and careers [1, 2]. Despite these possibilities, research [3] has noted that instructors struggle to balance the level of guidance required by learners while ensuring their instruction aligns with curricular goals and the experimental nature of making activities. In this study, we adopt theoretical approaches that focus on motivating teachers' actions in a specific role identity by elucidating the harmony (or lack of it) between the cognitive, social and affective aspects that impact teachers' adoption of the role identity [4, 5]. The research question asks: *What is the nature of environmental educators' identity exploration over time as a result of iterative design, development, and instruction of a maker-based course for environmental science?*

The Projective Reflection (PR) theoretical and pedagogical framework informed the design of the maker course and the assessment of teacher outcomes. PR conceptualizes learning in the 21st century as a continual process of change in an individual's identity, or a process known as identity exploration [6]. Four PR theoretical constructs support the exploration of identities across specific domains or career roles: (a) Knowledge and digital/technical literacy skills [7], (b) Interests/Valuing [8], (c) patterns of Self-organization/Self-control [9], and (d) Self-perceptions/Self-definitions [10]. The four constructs can be utilized to aid in tracking changes across an individual's exploration of role-specific identities (i.e. maker educator) as they repeatedly reflect on changing aspects of self across a teaching/learning experience.

2 Study Design

Invent with Environment was designed and implemented from Fall 2018 to Spring 2019 to help high school and middle school students to engage in the exploration of identities related to environmental science and art. Across 14 weeks of workshop activities, three environmental educators partnered with researchers to implement IwE activities. Participants Ashley and Edmond (pseudonyms) were recruited purposively as they were available for the duration of the intervention and expressed interest in adopting maker-centered learning into their instruction.

Quantitative Ethnography [11] was used to guide data analysis procedures and answer the research question. Researchers engaged in a deductive coding process for each teacher's chronological reflective data (short-answer question responses), in which each response was coded for the presence (1) or absence (0) of change or reflection on the self in terms of the four Projective Reflection constructs. Coded datasets were then uploaded into the Epistemic Network Analysis (ENA) web tool [12] to generate network visualizations of the associations teachers drew between identity constructs over time. In-depth qualitative examinations of each teacher case [13] were also conducted to contextualize teacher changes in the networks over time.

3 Results

Ashley demonstrated much stronger connections to knowledge over the first half of the IwE program as all her connections to knowledge are stronger in Time 1 (green). Prior to the first professional development, Ashley highlighted connections between knowledge of environmental science, technical literacy with making technologies, and facilitating student interest in environmental science, "To be successful in this role, one would have to have a basic knowledge of learning by making and then a passion for exposing students to the environmental science field." In the second half of the IwE program, Ashley reflected on her own role as an educator, "One major goal that I have in my role is for students to feel connected to the natural world and feel as though they have stake in solving environmental problems." Through these qualitative exemplars, Ashley's shift from knowledge orientation to orientation towards her own self-organization and self-control is detailed.

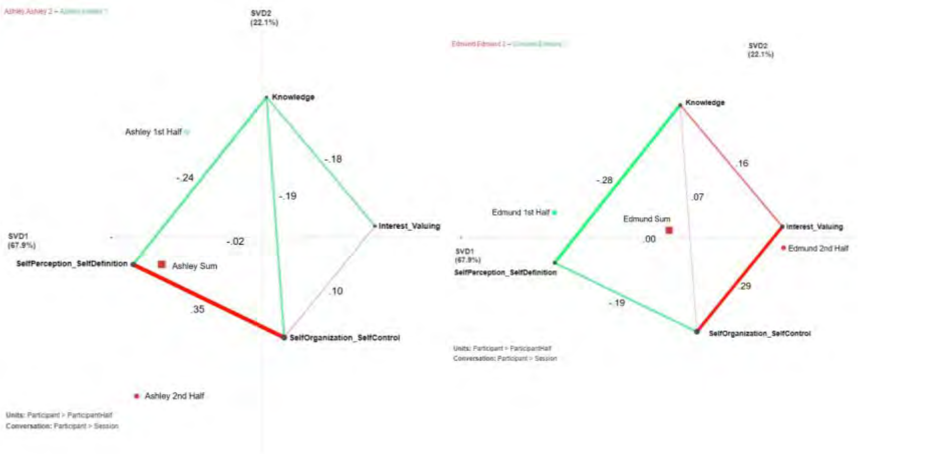

Fig. 1. Difference model for Ashley (left) and Edmund (right) in which associations from Time 1 (green) are subtracted from Time 2 (red).

Edmund began the first half of the program demonstrating relatively strong connections between his self-perceptions and self-definitions and the other three PR con-structs. This is unusual for PR data as individuals generally require extended periods of time to elucidate their specific roles. Edmund, however, began the intervention with a relatively strong sense of his role as an educator despite the added integration of the maker curriculum: “First understand that all the kids must be treated the same way disregarding their origin, background etc. Give them time to analyze. It's ok to ask questions, and it’s ok if they don’t know the answer. Make them feel welcome.”

In the second half of the program, Edmund demonstrated stronger connections to his interests and values: “Be open to listen to the concerns of the students and be very flexible. Flexibility is very important to be able to transmit to the students that it is ok to not know everything.” Throughout the program, Edmund demonstrated distinct interests in his role as a mentor to students even going so far as to offer insight on how to apply for internships and camp counselor roles for interested students. His epistemic networks and shifts from time 1 to time 2 indicate a more specific and more explicitly and repeatedly affirmed development of his interests and values over time.

4 Discussion

Findings from the Invent with Environment program revealed changes from each instructor’s Starting Self to New Self were identified through Projective Reflection as a result of their participation in the intervention. In general, Ashley followed a more “traditional” identity exploration trajectory as defined by Projective Reflection. While she began by demonstrating stronger connections to knowledge, her trajectory shifted to be more focused on self-organization and self-control construct by the end of IwE. As evidenced previously, Ashley discussed her encouragement of student-led exploration. This suggests that as Ashley’s own identity as an environmental educator shifted to integrate making activities into her instruction, her approach also shifted to integrate a more constructionist perspective in support of learning by making [14].

While Edmund experienced a less traditional trajectories in terms of identity exploration as defined by Projective Reflection, his experiences reveal potential pathways of similar educators attempting to integrate making activities into their instruction. Specifically, these non-traditional identity exploration pathways require additional investigation in order to aid in understanding and interpreting the various trajectories educators undergo as they seek out ways to integrate making into their instruction. This outcome suggests that additional supports (e.g. longer and/or more targeted professional development, additional curricular development time) may be required in order to facilitate a more balanced identity exploration trajectory.

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Doctoral Consortium

Coding Video Data to Develop Temporal Multimodal Epistemic Frames from STEM Activities

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Abstract. Video data allows for the capture of dynamic, temporal and complex interactions within face-to-face learning environments such as STEM activities. In order to temporally analyze both activity navigation and modes of meaning-making, a flexible tool that can combine multimodal evidence of object networks and epistemics for subject knowledge and 21st century skills is needed. This paper presents a possible method for coding video data into multimodal cognitive and skills-based frameworks that can be analyzed using combined advances in epistemic network analysis (ENA) such as the Multimodal Matrix and Moving Stanza Window methods. Using ENA to provide quantitative evidence for social semiotic learning frameworks allows for the analysis and visualization of temporal network data that can help reveal interactional patterns between the various epistemics and objects present within complex STEM learning contexts. By exploring these various networks, it is possible to provide empirical evidence for identifying the conditions for learning that underpin STEM education. Richer and comparative evidence outlining what actually takes place over the course of STEM activities for the various actors involved will help to develop and refine current STEM learning theories and practice that are too often influenced by traditional assessment and intervention methods of investigation.

Keywords: STEM, multimodality, epistemic network analysis, video data, 21st century skills, social semiotics, Multimodal Matrix, Moving Stanza Windows

1 Goals of the Research

The purpose of this research is to exploratorily map and analyze collaborative STEM learning by combining advances in epistemic network analysis (ENA) such as the Multimodal Matrix [1] and the Moving Stanza Windows method [2].

2 Background of the Project

As STEM education becomes vital for participation in knowledge-based economies [3], it is important to understand how to better shape effective STEM learning. Studies into STEM fail to fully explore the interplay between skills and knowledge epistemics within the object interactions captured in video data [4]. The use of multimodal social semiotics is effective for understanding meaning-making and contextual navigation [5], however this approach lacks the quantitative analysis of interactions found in ENA.

3 Methodology

This mixed-methods project uses a case study research design. One case is a two-hour hack-a-thon to build and program model electric cars and the second case is a ten-day design sprint to prototype digital solutions to real-world business problems. Two randomly selected groups from each case were recorded using stationary GoPro video cameras. Each group consisted of one mentor and between four to six participants. Around 80 hours of video data was collected. The video data is transcribed for verbal and multimodal utterances using Transana Pro, which allows for the analytical keyword coding of theoretical constructs. Transcriptions will be further coded into ENA format using Multimodal Matrix and Moving Stanza Windows methods.

4 Expected Findings

Mapping temporal and multimodal interactions will hopefully uncover the interplay between 21st century skills and knowledge epistemics at critical moments within STEM learning activities. These patterns should reveal opportunities to improve on possible gaps between STEM learning theories and the actual meaning-making for participants.

5 Expected Contributions

This project aims at contributing to research on effective STEM education by departing from assessment and intervention methods of investigation. Using ENA to analyze videos that map interactions within STEM activities allows for social semiotic learning theories to be informed by quantitative, rather than only qualitative, evidence.

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Learning with the Internet: A Mixed-methods Study of Computer and Software Engineering Students' Learning with Non-curricular Resources and Digital Tools

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Abstract. The aim of this research project is to understand how computer and software engineering students use online resources that are common among professionals to enact their learning practices. I combine different types of data and methods to first map their learning practices, and then to characterize the process through which they come to be enacted in time by implementing a mixed latent transition analysis (mLTA). A list of common uses given to different online resources by professional software developers is used as the basis for designing the data collection instruments. Data is collected from students in undergraduate programs in Norway. It is expected that the mLTA will allow exploring the process through which the students enact learning practices similar to those typical to professionals' work, differences among the students, and the purposes and contexts that influence their enactment. The results from the mLTA will be used as the basis of a design based research study that will be implemented in a software development course to test different ways of supporting students when using these resources during their studies.

Keywords: Learning Practices, Latent Transition Analysis, Design Based research, Digital Technologies.

1 Goals and Background of the Research Project

Higher education students' use more and more online resources that are not included in their curriculum in their learning practices. Nevertheless, although research has suggested that the use of these types of resources influences student learning [2][4], we know little about the process through which this happens. This research project's main aim is to understand how computer and software engineering (CSE) students enact learning practices and capitalize on these online resources. More specifically, I give attention to learning practices that relate to practices common among professionals in this domain. Professionals in the CSE domain rely on complex software ecosystems for their work [5] and CSE students have been observed relying on those same online resources during their academic tasks, even if they were not included in their curriculum [3]. The project takes an ecological perspective on learning practices, arguing that students enact them by engaging with practices available to them in their environment (i.e. school, Internet, etc.). The main goals of this project are (1) to understand how CSE students use online non-curricular resources for their own purposes across contexts to enact learning practices and (2) to test ways to support them within the curriculum-based learning, by using mixed methods and a design based research study.

2 Methodology

Mixed methods that combine different types of data have been used widely in the field of research on human factors and ergonomics in health care [1]. This project takes a similar approach to study complex learning processes that extend beyond the boundaries of curricular design in undergraduate education by mixing stochastic process modelling with qualitative methods. The data collection instruments are designed based on a list of uses given to online resources identified as common among professionals in the domain, built based on different research projects' outputs. Mapping which of these same activities and resources are common among the students allows performing a mixed latent transition analysis, combining Markov-modulated Poisson processes and topic models to analyze survey data and digital traces, with qualitative analytical methods on group interview data. Data collection is first scheduled for October 2020, and the results will be used as an input for a design based research study to be carried out in 2021 to test support mechanisms for the use of these resources within the curriculum.

3 Expected Findings and Contributions

I expect to find that students' learning practices align to practices of their professional domain in different ways, influenced by the students' own purposes and the context in which the practices are enacted. I also expect to find that undergraduate education can offer support for the use of online resources and that it can improve student learning. The study contributes to the field of quantitative ethnography by exploring how different stochastic process modelling methods can be used in combination with qualitative methods to study complex learning processes. It also contributes to the research area on student learning in higher education by improving the understanding of how the use of digital technologies can support learning beyond the boundaries of the classroom.

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Online Support and Antidepressant Sexual Side Effects

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Abstract. Sexual side effects of antidepressants (ADs) significantly impact patient quality of life and contribute to antidepressant discontinuation. The online social media site Reddit offers unique data on these side effects because user semi-anonymity promotes self-disclosure and disinhibition. This study uses data from the Reddit subcommunity r/depression to modify and extend the Social Support Behavior Code, a support classification model which has previously been applied to online discussions of health. Epistemic network analysis is applied to quantitatively evaluate the relationship between support strategies and AD types in discussions of AD-related sexual side effects. Preliminary results indicate that support in posts and immediate replies to posts (top-level comments) differ for threads which discuss the most commonly prescribed type of AD, selective serotonin reuptake inhibitors (SSRIs), other types of ADs, or both SSRIs and other ADs. Additional analyses will include other types of ADs and will evaluate responses to top-level comments from post authors.

Keywords: antidepressant, epistemic network analysis, side effects

1 Background and Goals

Antidepressant (AD) sexual side effects (SEs) are major barriers to AD use, significantly impact patient quality of life, and may lead to AD discontinuation [1-9]. Frequency of sexual SEs are often reported to be more than 25% but vary widely, in part due to methodological differences and stigma associated with sexual dysfunction [1-9]. Social media sites such as Reddit present a unique avenue to collect data on AD sexual SEs because user semi-anonymity promotes self-disclosure and disinhibition [10].

The Social Support Behavior Code (SSBC) has previously been used to analyze online health discussions [11-14]. It consists of 23 codes (in *italics*) divided into five groups [15]. Tangible support includes indicating a *willingness to help* or do an activity with someone (*active participation*) and offers to *loan* something or perform a task that benefits another person (*direct* and *indirect tasks*). *Suggestions/advice*, *referrals*, *teaching*, or helping someone reframe their situation in a more positive light (*situation appraisal*) are informational support. Network support focuses on offering *access* to others or reminding someone of the *presence* or *companionship* of others, and esteem support includes *compliments*, *validation*, and reassuring someone they are not to blame (*relief of blame*). Emotional support types are *prayer*, *encouragement*, *sympathy*, *physical affection*, *understanding/empathy*, reminding someone of their *relationships*, *listening* attentively, or assuring someone of a conversation's *confidentiality*. This study modifies the SSBC and uses epistemic network analysis (ENA) to quantitatively evaluate the effect of AD type on support strategies in discussions of sexual SEs of ADs.

2 Methods, Preliminary Results, and Expected Contributions

Threads with posts referring to AD sexual SEs were collected from r/depression based on AD keywords with the Python Reddit API wrapper [16]. Codes were developed and validated iteratively. SSBC codes in this study (underlined) are sympathy, referrals, encouragement, advice, teaching, prayer, and situation appraisal. *Access*, *presence*, *willingness to help*, *companions*, and *relationship* support codes were merged. *Understanding/empathy* and *validation/agreement* combined to form cognitive empathy. Affective empathy referred to shared experiences, and individual experience support occurred when a redditor discussed an experience without comparing situations. ADs, sympathy, referrals, and encouragement were coded with the R package nCodeR ($K > 0.75$, Shaffer's $\rho < 0.05$), and ENA graphs were created with rENA [17-21].

Subtracted weighted network graphs (Fig 1) reveal connections based on AD type for support codes which occurred at least ten times. Axes correspond to the single value decomposition (SVD) dimensions which account for the most variation in the data [22]. On SVD2 (y-axis) but not SVD1 (x-axis), threads discussing non-SSRI ADs (black) differ significantly from those referencing SSRIs only (purple, Fig 1A, Dunn's $Z = 1.9850$, p-value = 0.0354 adjusted with false discovery rate [FDR]) or referring to both SSRIs and other ADs (red, Fig 1B, Dunn's $Z = 3.6388$, p-value = 0.0004 adjusted with FDR). Requests for advice, offers of advice, and offers of affective empathy are more common in threads on SSRIs only (Fig 1A) or on both SSRIs and other ADs (Fig 1B) compared to threads discussing only non-SSRI ADs. These threads typically consist of a post asking for advice on addressing sexual SEs, comments echoing the posters' experience, and a mix of advice to switch medication or to continue taking the prescribed AD. Threads on non-SSRIs tend to request individual experiences and provide teaching more often than those discussing only SSRIs (Fig 1A). SSRIs are the most commonly prescribed type of AD [23], so this may reflect posters' lack of familiarity or first-hand experiences with non-SSRI ADs. Compared to threads referencing both SSRIs and other ADs, threads focused on non-SSRI ADs more often include affective empathy requests and offers (Fig 1B). This typically consists of posts asking if others also experience sexual SEs and comments affirming this experience, which may suggest users are less familiar with sexual SEs of non-SSRI ADs compared to SSRIs.

This study extends prior work by adapting the SSBC to communication about sexual SEs of ADs. To the best of my knowledge, this is also the only study to apply ENA to Reddit data. Continuing analysis will assess the impact of support and AD types on replies to top-level comments.

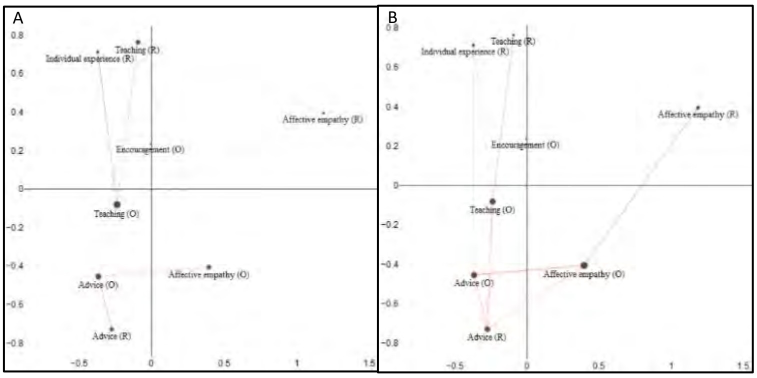

Fig. 1. Subtracted weighted network graphs showing differences between threads discussing A) non-SSRI ADs (black, n = 42) and SSRIs only (purple, n = 47), or B) non-SSRI ADs (black, n = 42) and SSRIs and other ADs (red, n = 66). Support types are requested (R) or offered (O).

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How to Elicit Computational Thinking through Modeling

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Abstract. As the world increases the use of technology, it is imperative that students understand and work with computational thinking as a common core. With the use of Model Eliciting Activities we are able to elicit the understanding of CT in students of all ages. Students develop models that help them understand the technical concepts and acquire the skill set that they will need to become successful in further studies and in the workforce. Epistemic Network Analysis gives us the opportunity to analyze great amounts of data that was collected during the process of developing the MEAs.

Keywords: Computational Thinking, Model Eliciting Activities, Epistemic Network Analysis.

1 Goals of the research

The purpose of study is to understand how computational thinking is elicited through the use of model eliciting.

2 Background of the project

The term computational thinking is defined as the processes in formulating problems and their solutions so that they can be effectively carried out by anyone, it is a fundamental skill that everyone should have, not only computer scientists. It should be included in the K-12 curricula as a core subject. It has been identified as a critical competence. The Next Generation Science Standards (NGSS) include computational thinking as one of eight core scientific practices (Jang, 2016; Tang et al., 2020; Wing, 2006).

Model Eliciting Activities solve complex problems that call for multiple cycles of interpretation until the solution is understandable and useful for the different stakeholders. MEAs are prepared so students can work with problem solving strategies that serve as descriptors of problem-solving behavior, the students work in different iterations of the problem until they produce the answer that best fits the solution for the problem. The creation of models by the students, provides opportunity to interpret thinking and gives them the opportunity to rethink their answers. Problem-solving strategies can be used for instructional purposes.

3 Methodology

In this pilot study we collected data from students in a San Antonio, TX, high school. The methodology we are using is quantitative ethnography, as described by Shaffer (2017) it helps us understand the concepts, the networks developed and the way students elicit knowledge in a data-rich environment. We are able to understand the thinking process of the students through the observation and analysis of the discourse during the development of the MEA. We are able to analyze all the information in their conversation by combining ethnography and statistics (Shaffer, 2017).

The discourse between teams was analyzed using Epistemic network analysis (ENA). With ENA we were able to model the association between elements of complex thinking. MEAs are activities designed for small groups, the connections among cognitive elements is key to the analysis. Using ENA we were able to examine the connections and visualize to identify patterns and to represent the co-occurrence of concepts within a conversation. (Buckingham Shum et al., 2019; Shaffer et al., 2016; Siebert-Evenstone & Shaffer, 2019)

4 Expected Findings

In the pilot study we confirmed that the students are having conversations that demonstrate their knowledge and understanding of computational thinking concepts. Students mainly talked about pattern recognition and abstraction while working on their Model Eliciting Activities. Preliminary findings tell us that the students worked through the key aspects of computational thinking. The students discuss pattern recognition, they identify the repetitions on the process and are able to create a rule that will later on become an algorithm.

5 Expected Contributions

Epistemic Network Analysis will help us determine the different interactions between students and how they achieved the goal of developing a model. There are many aspects that are being developed while working on MEAs, different concepts surge and the team members self asses the best and most efficient solutions to the problems. ENA will help understand all the concepts and abilities developed during the MEAs.

The students will be able to understand the use of Computational Thinking in an activity that is meaningful and familiar to them. These characteristics will allow a purposeful learning activity that will help them replicate their understanding in other environments with higher technical difficulties. The students will understand the basics of computational thinking

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Early Career Workshop

An Exploration of Patient Decision-making via Epistemic Network Analysis

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Abstract: Patients regularly choose between employing conventional and non-conventional medicine to treat their illness, yet this decision-making process is not well understood. Thirty semi-structured interviews were conducted with patients in four illness groups to explore said decision-making processes. Narratives were coded with the aid of the Reproducible Open Coding Kit and modelled with Epistemic Network Analysis. Preliminary results show a significant difference between users of biomedicine and non-conventional medicine in terms of lay etiology. The expounded results hope to contribute to doctor-patient communication regarding therapy choice.

Keywords: Epistemic Network Analysis, Semi-structured interviews, Therapy choice, Patient decision-making.

1 Goals of the research

The primary objective of this initiative was to understand the interplay of psychological and sociocultural factors underlying choice of therapy (conventional versus non-conventional medicine).

2 Background of the project

Non-conventional medicine (Complementary and Alternative Medicine, CAM) use is prevalent throughout the Western world (1). Albeit most patients consider these as augmenting therapies, a growing number of individuals (up to 30% (2)) employ CAM to the exclusion of biomedicine. If patients forgo conventional therapy when faced with life-threatening disease, the exclusive use of CAM endangers the individual and can be referred to as “dysfunctional CAM use” (3). CAM modalities are not a mere product or service, but a set of beliefs and values embedded within a larger cultural-behavioral system (4). In order to understand therapy choice, the interplay of relevant factors must be explored.

3 Methods

Semi-structured interviews were conducted with patients via non-proportional quota sampling, stratifying on therapy choice, primary diagnosis, and sex. Data collection began in 2019, in Budapest, Hungary. Each interview addressed the following topics: Epistemology (sources of health-related information), Ontology (lay etiology), and Behavior (patient journey). Transcripts were coded deductively with the Reproducible Open Coding Kit (rockbook.org). To map relevant constructs and emergent patterns, we chose Epistemic Network Analysis (ENA) as our analytical method. For a more detailed methodological description please see Zörgő&Peters (5).

4 Preliminary findings

The biomedicine and CAM groups show a significant difference in their lay theories of illness causation, especially with respect to the code "vitalism". Albeit this difference in lay etiology still stands when comparing male and female networks, there does not appear to be a significant difference among illness groups. Thus, belief in vitalism (as part of lay etiology) may be a crucial factor in therapy choice.

5 Expected contributions

Through the mapping of patient cognition concerning therapy choice, recommendations can be developed to aid doctor-patient communication and increase patient safety.

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Temporal Analysis of Discourses in Knowledge-Creation

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Abstract. This study examines how to perform temporal analysis of discourse data as a basis for development of a temporal analysis method for knowledge-creation. This study uses the combination of socio-semantic network analysis (SSNA) and in-depth dialogical discourse analysis. A comparative study was conducted by analyzing the same dataset using the previous method and the proposed method. The main finding is that the proposed method of this study, unlike the previous method, is effective in visualizing transitions of ideas during learning activities.

Keywords: Knowledge-Creation, Temporal Analysis, Discourse Analysis, Network Analysis, Socio-semantic Network Analysis.

1 Background and goals of the project

This research project aims to develop a temporal analysis method for understanding knowledge-creation. In learning as knowledge-creation, learners are required to create ideas and improve them collaboratively. Thus, educators must consider learners' discourses temporally to assess they engage in improvement of ideas. This study has used the combination of socio-semantic network analysis (SSNA) and in-depth dialogical discourse analysis.

When using SSNA to analyze ideas improvement, the total value of the degree centralities (C_d) is used as a measurement of ideas improvement [1]. The C_d score shows how keywords create clusters. Most previous SSNA only perform aggregative analysis, and little is known about temporality of ideas improvement. However, many studies across disciplines have discussed the problem of ignoring temporality. Hence, there is a need to develop and examine temporal methods in combined quantitative and qualitative approaches to studying learning as knowledge-creation.

2 Methodology and preliminary findings

A comparative study was done by analyzing the same dataset using the previous method and the proposed method. The datasets are tenth-grade students' discourses in collaborative learning on the human immune system that were gathered during their regular biology class. In this class, students discussed the question "Can you explain how vaccinations protect us from infections?" Thirty-nine students participated, with

12 groups of three or four students. This study chose the data based on their conceptual understanding of their post-tests.

The most important preliminary finding is that the proposed method is an effective means of visualizing transitions of ideas during learning activities (Fig. 1). Thus, this study has shown that the difference between the previous SSNA and the proposed method, and the effectiveness of timestamp information [2-3].

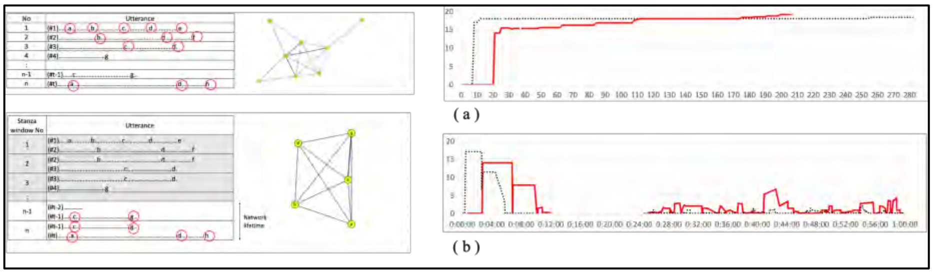

Fig. 1. The difference between the previous SSNA (a), and the proposed method (b): analysis data with timestamp information by SSNA combined with the moving stanza window method (window size = 2) and the network lifetime (lifetime = 2) [3]. On the left side, the keywords networks after the last analysis are shown. On the right side, the transition of C_d is shown; the vertical axes represent C_d; the horizontal axes represent the number of utterances or time; the high learning outcome group is shown by the red line and the low learning outcome group by the black dotted line.

3 Expected contributions

This research contributes to the assessment of improvement of ideas in order to design educational materials, instructions, and learning environments. From the results of this research, it is confirmed that the proposed method elucidates the peaks and troughs of ideas improvement through time. Additionally, the results show that analysis using timestamp information is effective for assessing the similarities and differences between groups [3].

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Understanding Identity Change in Game Affinity Spaces

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Abstract. This work examined patterns of identity change enacted on a community forum for the game *Kerbal Space Program.* Social network analysis (SNA) visualized forum friend groups, which highlighted members with high and low social centrality for case study sampling. To understand identity exploration as a form of complex thinking, Epistemic Network Analysis (ENA) visualized patterns of association across identity constructs as defined by the Projective Reflection framework. Integration of SNA and ENA (SENS) and case studies illustrated how most and least socially central participants enacted personally relevant and socially situated identities, with high centrality members emphasizing interests and values, and low centrality members giving or receiving social regulation. Findings offer insights into the field of games and identity, including new theoretical understandings, practical applications, and methodological approaches.

Keywords: Identity, Games, Social Network Analysis, Epistemic Network Analysis, Case Study.

1 Goals of the Research

The purpose of this study was to examine patterns of identity change enacted by participants on a community forum for the space flight simulation game *Kerbal Space Program (KSP).* Identity exploration is a valuable skill for 21st century learners [1], and game affinity spaces such as community forums hold promise for supporting role-specific identity exploration [2] but remain underexamined.

2 Background of the Project

The Projective Reflection framework conceptualized identity change in the community forum as “the deliberate internal or external action of seeking and processing information in relation to the self” [3, p. 250]. The model frames identity change as associations between four constructs over time: (1) Knowledge, (2) Interest and Valuing, (3) Self-organization and Self-control, and (4) Self-perceptions and Self-definitions [4].

3 Methodology

KSP and the community forum (the study site) were selected for their potential to support exploration of relevant identities. After using a web-scraping script to mine public player data from the forum, social networks (SNA) of player friendships were generated to understand the social makeup of the community. Extreme cases (most and least socially central) were then selected to develop qualitative case studies that illustrated processes of identity change. To understand connections that players made as they reflected on aspects of their shifting identities, Epistemic Network Analysis (ENA) visualized shifts in associations between the four Projective Reflection constructs over time.

4 Findings

Integration of study findings illustrated how participants often began with a focus on knowledge and interests, and by setting goals and working towards them, developed awareness of the self in the social context. Cases with high social centrality were more likely to affirm interest in and valuing of the space as a tool to meet socially situated goals, while those with low centrality enacted more regulatory behaviors (help-seeking or peer moderation). Along the X axis, a Mann-Whitney test showed that ENA data for cases with High Social Centrality (Mdn=-0.78, N=4) was statistically significantly different (alpha=.05) from Low Social Centrality (Mdn=1.55, N=4 U=3.00, p=.20, r=.63).

5 Contributions

Research on identity change in online spaces is vital as institutions are grappling with how to best support 21st century learners across their lives and careers. This work illustrates how game affinity spaces can support long-term personal transformation and offers insights into how to leverage these spaces to support situated, targeted, and intentional learning as identity change. This work has impacts as a methodological innovation in the field of Quantitative Ethnography as a practical example of the use of SENS.

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Symposia

Challenges and Solutions to Examining Twitter Data: Reflections from QE-COVID19 Data Challenge

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Abstract. In April 2020, the International Society for Quantitative Ethnography announced a week-long Data Challenge, inviting researchers from all over the world to collaboratively understand the implications of the COVID-19 pandemic on social discourse. More than 90 people from 16 countries collaborated in teams of 3-5 individuals in investigating questions ranging from government responses to shifts in educational practices. This symposium will feature presentations from four teams composed of researchers in academia and industry, with interest in anthropology, entrepreneurship, learning sciences, data science, to name a few. Each team examined a discourse that occurred on Twitter about COVID-19 by focusing on similar or unique culture-sharing groups. This proposal summarizes their investigations. The symposium uses the teams' experience of applying Quantitative Ethnography methods to delineate challenges and potentials of examining Twitter data. This discussion will be relevant to researchers particularly interested in (and new to) the examination of discourse on online platforms and the significance of applying QE techniques to data extracted from these platforms.

Keywords: Twitter Data, Quantitative Ethnography, COVID-19, Challenges, Solutions, Discourse

1 Quantitative Ethnography and Social Media

Shaffer's (2017) *Quantitative Ethnography (QE)* book introduced a research methodology to explore the patterns and connections within a discourse. Using QE, researchers can continue to apply the conventional techniques of ethnography, such as collecting extensive qualitative data (e.g., field notes, observation, etc.) to understand the rules of a particular culture-sharing group (Shaffer, 2017)—those properties that cannot be easily seen. In addition, QE affords quantifying qualitative data through a cadre of tools such as Epistemic Network Analysis (ENA) to capture the full pattern of non-projectable properties of a culture-sharing group (i.e., the properties that are beyond senses) (Shaffer, 2017). This symposium will feature presentations from four teams; each of them was participants in the COVID-19 Data Challenge organized by the International Society for Quantitative Ethnography. Each team examined a discourse about the COVID-19 pandemic on Twitter by focusing on similar or unique culture-sharing groups.

It is not surprising that Twitter data was used by the four groups during the QE COVID-19 Data Challenge. It is a popular social media platform, used widely for communication purposes for infectious diseases such as swine flu (H1N1), Ebola, and now COVID-19 (Kullar, Goff, Gauthier, & Smith, 2020; WHO, 2019). Users commonly use Twitter for sharing formal (e.g., advice from the World Health Organization) and informal medical information (e.g., advice from physicians). From an educational perspective, people use Twitter to interact with others and search for information, updates, and opinions. As such, Twitter yields an abundance of data generated rapidly by millions of users; an extensive analysis of Twitter data during pandemics provides opportunities for rich investigation. In addition, users generate hashtags, a form of metadata that is a useful tool for categorizing information around a specific topic. Researchers can follow hashtags to locate a thread of conversation around a topic (e.g., COVID-19) (Bruns & Burgess, 2011). Given these characteristics, Twitter data is amenable to QE techniques. Data can be segmented, coded, and visualized using QE techniques to identify the patterns among codes or individuals in a culture-sharing group.

For the QE COVID-19 challenge, scholars from different backgrounds collaborated on investigating Twitter datasets using their expertise in QE and data analytics skills. Four teams, working with similar data and encountering certain dilemmas, developed a proposal to further address their challenges and propose some solutions to them. Below, project summaries for each team are presented, followed by a section on the challenges encountered and the insights gained by these groups.

2 Project Summaries

Team 1 consisted of an entrepreneur, engineer, anthropologist, and biologist/learning scientist. They were interested in exploring the COVID-19-related content of Tweets from Donald Trump, the President of the United States, and the Centers for Disease Control (CDC) from January-April 2020, the time period when the COVID-19 threat was expanding and reaching pandemic status. The team found that although the CDC's message regarding COVID-19 stayed consistent over time, President Donald Trump's message changed significantly between January and April 2020. From January 15 to February 15, when the first official reports of COVID-19 infection occurred in the United States, President Trump's Tweets mainly focused on the economy, collaboration (meetings with state and local governments), and protection. In contrast, the CDC was tweeting about education, protection, and distancing measures. Testing became a higher focus for both entities over time. However, the general structure of the CDC networks remained relatively consistent over time. President Trump's network looked more like the CDC's network by March, although there is a strong emphasis on collaboration. One possible extension of this work is to examine long-term economic and health impacts of countries that had a unified message from the beginning of the pandemic, and those who did not.

Team 2 consisted of doctoral and undergraduate students whose research typically centers on learning analytics, educational data mining, learning sciences, and sociology. They were fascinated by the differences in how the United States public was responding to US leaders and COVID-19 policies on personal and political levels. Centering their investigation around the economic stimulus package that was announced on March 27, their dataset included Tweets collected by the open-access IEEE DataPort™ website from March 26 to April 1, 2020. This aid package, the largest in U.S. history, was implemented in order to mitigate the economic consequences of the COVID-19 pandemic by supporting individuals with one-time $1,200 direct payments and businesses with grants to discourage lay-offs (Kretchmer, 2020; Pramuk, 2020). The original dataset included 2,461,489 tweets and was filtered by mentions, replies, and retweets of the following politicians: Donald J. Trump, Mike Pence, Ron DeSantis, John Biden, Bernie Sanders, Andrew Cuomo representing politicians across the political spectrum. The final filtered dataset that informed the analysis included 32,610 unique Tweets, which was explored using the tidyverse R package (Wickham et al., 2019). Their initial findings indicated differences in how users connected personal perspectives with conspiracy theories and mitigation measures when directly addressing Trump, whereas users tended to connect disease experts and political groups when addressing Biden.

Team 3 consisted of learning science and data science researchers in academia and industry. They were curious about the impact of the current period on formal and informal educational practices across the spectrum. Anecdotally, they agreed that in a very short period, remote learning became a dominant instructional method for educational institutions, service providers, and key stakeholders (i.e., educators, parents, and students). They also believed that everyone involved in the process of education had to adapt to rapid shifts; thus, prompting them to engage in some behaviors as a response. Thus, they focused their inquiry on the Twitter discourse around #remotelearning, April 20 to April 27, during the pandemic. They investigated how various stakeholders in education were contributing to the discourse and responding to this massive shift in schooling structures. They started their analysis by grounding their understanding of the qualitative tweet content and users' bio. By going through the sampled excerpts, each group member-generated its own coding scheme and discussed its situated hypothesis in the group. Then, code schemes from individuals were merged and integrated into one. They developed the code names, conceptual definitions, and procedural definitions of a codebook describing twitter users' online communication behavior when they talk about remote learning. They also identified educational stakeholders by searching for keywords throughout the dataset. After code validation, they conducted ENA to compare behavioral patterns for different stakeholders. According to the statistical testing result, they found there is a significant difference between the teachers and EdTech companies in their behavior patterns when talking about remote learning on Twitter.

Finally, Team 4 consisted of educators and teachers. They investigated school closures due to the COVID-19 pandemic and several problems created by this pandemic for students, teachers, parents, school districts, and administrators. The data source was from the IEEE DataPort website; hence, API was not required for obtaining the data. In the U.S., the schools were officially closed from mid-March in response to the pandemic, and the education shifted to an online format at all levels. Team 4 decided to review the tweets of people to see what the most challenging themes are that people have talked about the most. Further, they wanted to see how time has changed peoples' views toward school closures and its consequences. To do this, they picked two time points in April and May and tried to compare people's tweets in terms of the structure of connections between the codes using QE techniques such as ENA (Shaffer, 2017). They found four themes that were discussed the most by people as related to school closures: school closure and people's reactions, distance learning/online education and the challenges it brought for students and teachers, homeschooling and the challenges that parents were facing, and the budget related tweets about the financial constraints or educational institutions and paying the wages of teachers and administrators.

Below we discuss common and unique challenges each team experienced and our collective reflection on possible solutions in applying QE techniques to Twitter data.

3 Challenges and Potential Solutions

3.1 Dataset Availability and API Permission

The first and most crucial step in working with Twitter data is obtaining a dataset or scrapping one from Twitter. For instance, team 4 and Team 1 used freely available datasets. However, some researchers might want to gain API access, which might take some time. There are three types of API which Twitter grants access to standard (which allows free access to the last seven days of Tweets), premium (allows free and sometimes paid access to the previous 30 days of tweets), and enterprise (paid access to tweets as early as 2006). While the standard API might be an excellent option for some researchers, access to datasets that are only seven days old might not work for research questions where the variable of time is important. One team used the dataset freely provided by IEEE and experienced numerous issues with hydrating the files and exporting them as a .csv file. Using an already hydrated file, the team sorted for the first twenty tweets, and the exported CSV file contains non-ASCII characters.

3.2 The Abundance of Data

Another issue is the abundance of data in Twitter datasets, which sometimes makes opening and handling datasets difficult. For instance, in one dataset, which was only for 1 hour, Team 4 found 920,076 tweets related to coronavirus. One solution is to narrow down research questions from the beginning and limit the scope of searches to specific keywords or hashtags or their co-occurrence. Another solution is to limit the scope of the tweets to particular hours or people or exclude the replies and retweets and only code the original tweets. If one is not sure what hashtags might be relevant for examination or what keywords might be related to one's research question, a small number of tweets can be extracted, followed by an inductive coding of these tweets by members of a research team. Based on those codes and themes, one can move forward and search for the hashtags or the keywords that are most pertinent. While some teams were trying to reduce the abundance of data, Team 3 was struggling with making full use of the scraped data stream. This team was interested in understanding how different roles of users behave in tweeting about remote learning during the pandemic. In their data processing, to keep the internal validity of the analysis, they removed users with multiple roles in their bios to reduce the potential confounding variables. This current method of addressing users with multiple roles resulted in failing to make full use of the abundant data. There are two potential solutions to this challenge for their next steps. 1) Natural Language Processing (NLP) can be conducted to identify which role is more dominant for a user based on the content of the tweets. 2) Coding for all roles can be conducted to derive combined role categories for different users. For example, if a user is both marked as mom and teacher, a new role such as "Family Member & Teacher" can be generated to distinguish from users who are only marked as "Family Member" or only as "Teacher".

3.3 IOS vs. Windows Issues

For iOS users, there might be a need to consider alternative ways of using hydrators and data scraping tools. Octoparse was a tool that was introduced by one of the team members during the QE COVID-19 Data Challenge, and it could be used to parse out Twitter data in an efficient way. However, Team 4 was not able to use it with Mac, and installing a virtual Windows was a challenging process which made the process of parsing slower. Finally, conventional methods of parsing Twitter data with Python were used, and we recommend doing so if you are a Mac user. A Mac alternative to Octoparse is a DocNow hydrator, which was used by Team 2 (for a beginner guide, see: https://programminghistorian.org/en/lessons/beginners-guide-to-twitter-data). The issue with hydrating data was also present in Windows, and this error "invalid tweet id online in [file path]" was seen multiple times. One solution to this problem is to change the format of the file from .csv to .txt. Also, there should only be one column in the .csv file, and eliminating the unnecessary columns will ease the process of hydrating Twitter data.

3.4 Lack of Well-designed Resources

The process of parsing out Twitter data can be done using multiple ways, but sometimes the resources were not well designed or well presented. For instance, the GitHub page for hydrators is not user-friendly, and only the latest version of hydrator (0.08) has downloadable files, while the other versions have not been removed. Furthermore, different tutorials have made various suggestions. Some require downloading multiple R or Python packages to be able to work with Twitter data. The only viable solution to this challenge, at least during the limited time of the Data Challenge, was to split the work of learning about different tools and reviewing all options to see which one is more efficient.

3.5 Coding at Scale

As noted above, Twitter datasets are plentiful, and rigorous filtering is needed in order to make them manageable in any sense. However, the diversity of data that originates at that scale provided several coding challenges for Team 2: (1) Creating relevant codes/regular expressions based on a small sample of tweets that can extrapolate to a larger dataset especially given the informal, colloquial nature of social media discourse. (2) Difficulties in validating codes in ever-expanding samples that perpetually present minor differences for consideration. (3) Lack of context for short utterances leading to ambiguity and indirect meanings. Additionally, many web-tools used for collaboration have limits in terms of file size, which forces considerations of how large a sample-size to pick. We began to address these challenges by integrating iterative and alternative approaches such as topic modeling, nearest neighbor algorithms, and other natural language tools. Topic modeling can help to show the various forms a concept takes in your data which can assist in the formation of regular expressions for use in automated coding tools like nCoder. Nearest neighbor algorithms can help pinpoint potential false positives and false negatives when refining regular expressions. For example, Team 2 was interested in how people were talking about workers during the pandemic. It was important to identify that essential workers, as well as front line workers, were equally relevant to the discussion. Once “workers” were identified as a desired concept while coding, a search in the larger dataset alongside the topic model allowed for faster identification of important words to refine our search.

3.6 Distribution of Discourse

While we can never fully predict the types or frequency of participation in the public discourse, we should be observant. For instance, Team 2 ran into an issue of one leader, Trump, dominating the discourse. While this is expected, it called into question whether we had an accurate representation of the public opinion. Were more people truly bringing Trump in, or was it more because of the initial filter of the dataset to only tweet with “COVID” in the text? The benefit of Twitter being open source is that they have a built-in filter that will allow you to search for different timelines for keywords, usernames, etc. This allows for a quick “reality check” against assumptions in downloaded data. The “live” nature of Twitter allows for close interaction between the researcher and the data. It also allows for viewing of threads and other limiting factors such as location or time zone.

3.7 Challenges in Discourse Segmentation

To prepare data for ENA, one needs to perform discourse segmentation, that is, dividing a narrative up into meaningful parts (Shaffer, 2017). In this process, at least three levels of discourse must be distinguished: utterance (smallest unit of discourse segmentation; coding occurs on this level), stanza (set of utterances; code co-occurrence is computed on this level), and source (individual or group to which a stanza or sets of stanzas belong). Yet, as with most narratives, it is difficult to determine the optimal manner of segmentation. Even working with Twitter data, groups differed in their definition of utterance (one Tweet vs. one sentence within a Tweet); and provided one has access to a whole Twitter thread, the question becomes even more complex. A thread can equally be considered a single utterance or a set of utterances. Individual tweeting can be seen as a source, and their tweets can be organized into time periods, or even topics, to constitute stanzas. These are just some ways to segment discourse, with no clear-cut answers. This does provide an opportunity for playful data manipulation, though, when working in responsive environments. Team 2 often found new and interesting insights as they changed the unit of analysis to consider leaders in place of political parties or redefining the group to which a given tweet belonged.

3.8 Challenges in Model Configuration of ENA

Segmentation also allows the researcher(s) to organize data and prepare it for use in ENA webtool. When employing ENA, one must determine the unit (what one wishes to see a network for), the codes (nodes of this network; network structure is created by the frequency of codes and the strength of their co-occurrence), and conversation (the frame within which code co-occurrences are computed). Generally, units and codes are easier to determine, as these are what one visualizes when imagining their network. Conversation, and an even more elusive component, stanza window, reside on a middle level of data segmentation that is more difficult to grasp. Some teams designated conversation as time, instructing ENA to compute code co-occurrences by grouping data based on hour, day, week, or month. Other teams used narrative content to define the conversation, such as the ID of single tweets or sources (people). However, time can be a controversial choice when segmenting social media data. For example, Team 3 argued that it might not be appropriate because social media data is generated from all over the world, with users spread across various time zones. Whether to segment the whole week of data as one conversation or segment by each day is another point of future discussion. Lastly, the manner of co-occurrence computation must be determined as well: moving stanza window, whole conversation, or infinite stanza. These signify different computation methods and also influence results to a large extent. For example, using Twitter ID as conversation and whole conversation as stanza window will yield very different results (and address very different phenomena) than using month as conversation and infinite stanza.

3.9 Determining a Meaningful Research Question

Research projects are usually designed based on the research question(s) that researchers want to address, and the question(s) will determine the optimal method of data collection and analysis. Yet, the structure of the QE Challenge reversed these steps: we had to generate a research question from already available data. Furthermore, the Challenge lasted one week, and this limited time created an urgency to find meaningful research questions that could be answered with the pre-selected or available datasets and the given methods. In addition, meaningful research question(s) are frequently posed in relation to a theoretical framework; however, e.g., Team 3 experienced difficulties in identifying such a framework for their investigation. Given the time constraints, they adopted a grounded theory approach to develop and refine their code scheme, only based on the empirical data. Nonetheless, there are available theoretical frameworks that can be employed for the deductive coding of online interaction behaviors, such as the theory of Community of Practice (Gray, 2005).

4 Conclusion

Discourses in online communities afford rich spaces for understanding discourse around broad and specific issues. In this symposium, four teams that partook in the QE COVID-19 Data Challenge examined Twitter data from multiple vantage points. Despite its short duration, the exercise helped the groups, individually and collectively, to delineate the challenges and potentials of examining Twitter data. In general, the challenges of working with Twitter data with QE techniques can be summarized into Twitter-specific challenges (e.g., API permission, IOS challenges, or data abundance) and discourse related challenges (e.g., segmentation, and thematic coding). Identifying these challenges is the first step in addressing them. This work may resonate with all in the QE-community, but most appropriate for those who are relatively new or have started researching Twitter data with QE techniques such as Epistemic Network Analysis.

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Quantitative Ethnography in the Clinic

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1 Introduction

Many of the most pressing challenges in healthcare are characterized by considerable complexity. Sub-systems of people and technology interacting in environments combine to complete health care processes, including the actual provision of care as well as supporting processes (e.g., environmental services). Those interactions are what dictate the success of health care processes - including facilitation of patient-centered care and decision-making, control of hospital-acquired infection, and management of care transitions - and thus cannot be functionally decomposed and improved through simple procedural approaches. That is, health care is a complex sociotechnical system, and research on health care needs to reflect that complexity [1]. Further, these complex systems are characterized by uncertainty and competing demands [2]: health care professionals and patients must make decisions with incomplete and/or uncertain information; understand and balance trade-offs; account for numerous demands, including those of patients, hospital administrators, and insurance providers; coordinate care across multiple contexts and caregivers; and exercise clinical judgment. Trainees must learn to do these while mastering basic knowledge and skills.

The coronavirus pandemic of 2020 brought global attention to the importance, fragility, and resilience of our health care systems. The QE-COVID Data Challenge demonstrated the ability of Quantitative Ethnographic (QE) methods to interpret health care-related data in a unique way, which can inform health care professionals about pertinent results. While the efficacy of QE methods in COVID-related data is being addressed by other symposia, this symposium directs attention to wider applications in health care where QE methods have been applied or can be applied with promising results.

2 Symposium Structure and Goals

In this symposium, we bring together five leading QE experts who are working in the health care domain. Each expert will discuss their ongoing work in various application areas: doctor-patient communication, shared decision-making (SDM), quality of care and patient safety, medical education for students and practitioners, policy-level decision-making and best practices. Our goal is to highlight the breadth of ongoing QE research in the health care setting. Through discussion with the audience, we hope to stimulate interest of other QE researchers in the domain, foster collaborations, and identify next steps to grow the impact of the QE community in health care. In addition, we expect audience members to leave with an appreciation for the trans-disciplinary nature of QE, as each speaker comes from a unique field (Zörgő: medical anthropologist; Ruis: historian of science, medicine and technology; Wooldridge: human factors and systems engineer; Jung: educational psychologist; Popov: team learning scientist).

2.1 Doctor-Patient Communication

Doctor-patient communication is a fundamental part of clinical work; it is ubiquitous throughout a physician's career and constitutes a pivotal aspect of effective healing. Patients primarily judge their doctors based on their manner of communication, and these interactions determine patient satisfaction to a great extent. Good doctor-patient communication has been shown to correlate with better cooperation and increased adherence [3], as well as improved patient health [4]. The doctor-patient consultation can be seen as an exchange of worldviews and explanatory models of illness (i.e the cause, meaning, and preferred treatment of illness).

Due to the fact that many issues in doctor-patient communication can stem from differences in explanatory models, hermeneutic analysis is needed to explore worldviews, distinct perspectives, and specific narratives to pinpoint misunderstandings, disagreements, and miscommunication. In large amounts of qualitative data (e.g. semi-structured interviews, focus groups), salient cognitive patterns are difficult to identify in a reliable way, as qualitative methods are tailored to in-depth examinations of smaller populations. Most qualitative analyses are detailed and take a multitude of factors into consideration. Patient explanatory models of illness, for example, depend on and interact with clinical characteristics (diagnosis, prognosis, available treatment options, etc.), demographic characteristics (patient age, sex, education, etc.), and psycho-social-cultural factors (values, beliefs, social network, information-seeking behavior, etc.) and so on [5]. In order to see which factors are most prominent and how they interact with each other, one needs an analytical method that captures this complexity. Epistemic Network Analysis (ENA) enables the visual inspection of a wide variety of interactions not only among patient attributes (e.g. clinical and demographic factors), but also among relevant psycho-social- cultural constructs within patient narratives. By creating post-hoc subgroups within a sample (via conditional exchangeability), prominent cognitive and behavioral patterns can be identified. A model of complex interactions in qualitative data within a single visualization denotes a useful analytical tool, but it also signifies a powerful communication tool. When conveyed to practitioners or medical students, the network models also serve as effective means of representing the results and elaborating recommendations.

2.2 Shared Decision-Making

Clinical use of SDM—to meaningfully engage patients in the determination of their own care through the process of collaborative deliberation with health care providers on treatment options and the alignment of decisions with informed preferences—is widely seen as ethically imperative [6]. Policy leaders promote SDM not only for ethical reasons but also to improve health care efficiency. In the United States, SDM is one of the most widely promoted strategies to (a) reduce overtreatment and inappropriate care, (b) improve patient satisfaction and compliance with treatment recommendations, and (c) reduce variance and inequity in care provision [7].

Yet as clinicians, ethicists, and patient advocates have argued, promoting or requiring widespread implementation of SDM through policy initiatives may have significant unintended consequences if we can't reliably assess whether and to what extent SDM is appropriately implemented. It is difficult to measure the extent to which SDM affects health care utilization because there are no effective assessments of the SDM process that can be reliably applied at scale. For example, it is unknown whether SDM reduces unnecessary or inappropriate surgical procedures because there is variability in the extent to which SDM is implemented in clinical practice, and there are numerous, complex factors affecting health care utilization that may override the ability of SDM to determine care. Understanding the relationship between SDM and health care utilization requires large, multi-site studies, as SDM is used variably and effect sizes may be small. In the absence of such studies, policies that promote SDM may incentivize a model of decision making that addresses neither clinical nor ethical aims. To understand whether and to what extent investment in SDM affects health care utilization, new measures are needed that can assess whether, how, and to what extent SDM occurs in clinical encounters at scale.

QE provides an approach that could address this significant measurement challenge in health care. SDM is typically assessed either through patient surveys, which capture outcomes better than processes and often overestimate the extent to which practices like SDM are implemented [8], or through expert observation, which is costly and time intensive. Thus a key challenge is to develop reliable computational models that can replicate experts' qualitative judgement, making it possible to conduct more objective assessments of SDM at scale. Because, SDM is characterized by discrete discourse elements, linear (though iterative) progression, discursive interaction, and collaboration, QE provides a rich framework for developing such models. Research in QE suggests that classification algorithms can be developed that reliably identify key indicators of SDM, and ENA and techniques for modeling sequential patterns can capture interaction, progression, and collaboration. Indeed, this approach has proved valuable in assessment of clinical performance [9, 10], and extension to patient-clinician communication is a key next stage in the development of novel assessments in health care.

2.3 Health Care Quality and Patient Safety

Health care has a quality and safety problem: as many as 440,000 people die due to preventable medical error in United States Hospitals each year [11]. However, improvement has not been easy. Health care is a complex sociotechnical system – in order to achieve improved outcomes, we must consider interactions, relationships and interfaces between sub-systems and system elements [1]. Disciplines such as human factors and systems engineering – which focus on designing and optimizing systems and systems of systems – have tools, methodologies and theories to successfully apply systems thinking and make demonstrable progress [12]. The impact of these methods would be enhanced by improved ability to understand, analyze and visualize relationships and interactions between and within systems. QE unifies qualitative and quantitative data and methods to rigorously understand, analyze and visualize human cognition, behavior and interactions. Thus, QE is posed to make substantive contributions through methodological tools and philosophical underpinnings to make progress in improving quality of care and patient safety, in particular when applied in combination with human factors and systems engineering knowledge, theory and techniques.

One example of such an application is the interface in between systems in health care, i.e., the care transition. Care transitions are transfers of information, authority and responsibility for patient care from a clinician or a group of clinicians to another and are opportunities for information loss and harm as well as error detection, correction and resilience [13]. QE brings many approaches that could be used to improve care transitions. For example, ENA can help model and quantify relationships between system elements and factors that influence care transitions as well as accompanying communication and coordination processes. These models are useful to compare and evaluate different system designs as well as different stakeholder groups, e.g., with an in-person handoff or not or perspectives of different clinical disciplines.

2.4 Medical Education

Medical education has begun to move to competency-based training programs [14]. In such programs, milestones that physicians should be able to achieve independently by the end of their training period are identified. Then, mechanisms for training and assessing these competencies while allowing for individualized and formative feedback are developed. This form of continuous formative feedback on performance is becoming the norm in undergraduate and graduate medical education. However, once they have completed their training, practicing physicians are largely left on their own to figure out how best to keep current with their practice and learn new knowledge and skills. All practicing physicians need continuing certification activities (CCA) in order to maintain their medical license, but the suggestions provided for doing so are diverse and often lack evidence of effectiveness [15]. As such, CCA as part of Continuing Medical Education (CME) is moving toward specialty-specific experiences based on individual learning needs. CME in surgery is working towards achieving a tailored approach, utilizing individualized methods, such as coaching and simulation training. Practicing surgeons seem to have different needs based on their experience, and as they gain experience, appear to focus less on what not to do or errors and focus more on how to handle complex situations [16]. While in-person or video-based coaching or simulation training may be viable alternatives to historical forms of CCA, we currently do not understand how the interactions and conversations between trainers, mentors, or coaches and practicing surgeons working on developing new knowledge or skills influence the success of individualized CME [17]. This can be a particular challenge if these interventions are done remotely or asynchronously. QE can be a tool for developing models of these relationships and interactions. For example, research is beginning to provide insight into characteristics that may make people particularly good coaches. However, we do not know what about their coaching interactions make them especially effective. By modeling these conversations using ENA, we can explore not only what components of these learning sessions are important but how connections among elements in the conversations may impact successful CME relationships. These methods can also apply in other professions that require continuing education, such as law, counseling, or architecture.

2.5 Policy

The American College of Surgeons Accredited Education Institutes (ACS-AEI) provides a variety of learning experiences for practicing surgeons, surgical residents, and medical students using simulation-based education. Since 2005, ACS-AEI Consortium established standards for how simulation-based surgical training should be offered at Accredited Education Institutes in order to improve patient safety and promote the development of new techniques, technologies, research, and collaboration. As a part of the accreditation process in 2011 the ACS-AEI also added the identification of best practices to recognize centers for their innovations as well as to share these practices and advance the field. Best practices are viewed as “areas far exceeding the accreditation standards or novel methods of advancing high quality, impactful education” [14]. The ACS-AEI as an organization began to collect and systematize all best practices from accreditation reviews for dissemination to members of the ACS-AEI Consortium. Essentially, the ACS-AEI organization provides a forum for its members to share and learn from innovative approaches to common problems in simulation-based surgical training, ranging from curriculum development and evaluation to management and governance models and scholarly activities that advance the field of surgical education. In addition to sharing these innovative approaches, the compiled list of 337 best practices provides a rich source of data to understand not only the evolution of the field over a decade but also the evolution of the accreditation process and organizational perspectives.

ENA, a quantitative ethnographic technique for modeling the structure of connections in data, is a well-suited methodological approach to gain deeper insights into the communications from an accrediting body to its individual members over almost a decade. ENA is usually applied to systematically identify a set of meaningful features in the verbal and nonverbal data sets of individuals or teams [18]. Literature reviews, videos, newsletters, and workshops, comparative analysis of accreditation data have been previously utilized to compare postgraduate program accreditation processes. However, ENA is a useful technique for modeling how the ACS-AEI is communicating to its members because it can model the relationships between all best practices as they occur within the accreditation reviews, and therefore understand how the accreditation process is changing over time. ENA methods are generally applicable to other domains and disciplines by utilizing the power of dynamic network models. Importantly, insights gained from studying medical education and healthcare setting can be applied to a wide range of other high-risk industries, such as aviation or energy production.

3 Conclusions

In academia, one frequently encounters the divide between quantitative and qualitative research methodologies. Specifically in health care, the former is commonly thought of as more “objective” and “scientific”, while the latter is conceptualized as “subjective” research yielding “soft data” that does not easily lend itself to clinically relevant findings. This methodological dichotomy shrouds a difference in worldview as well: quantitative methods often adhere to the positivistic worldview (succinctly: there is one reality/truth, which can be measured, understood, controlled), and qualitative methods to the constructivist worldview (succinctly: social reality is co-constructed, there are multiple truths). These philosophical stances seem dichotomous, but the pragmatist appreciates that they are instrumental in answering vastly different research questions. Quantitative methods are apt for questions such as how often a certain phenomenon occurs, while qualitative methods are appropriate for answering what a phenomenon means to those experiencing it. The ability to address both “horizontal” (frequency of a phenomenon across a population) and “vertical” (meaning and context of a phenomenon) dimensions usually comes at a price: if one broadens their horizon of scrutiny, they inevitably sacrifice depth and vice-versa. QE caters to the epistemological preferences of positivistic, constructivist and pragmatist sensibilities by undertaking the unification of methodologies (via contextualized numbers and quantified narratives) and the unification of domains (breadth while maintaining depth). This unified methodology is especially well-suited for research in health care, as it is always from the interplay of biological, psychological, social, and cultural factors that illness and healing emerge.

QE and associated techniques, such as ENA, also provide a way to summarize and compare qualitative findings in ways that are digestible to those not familiar with qualitative research. Key differences and patterns can be represented, displayed, and discussed with clinicians and other stakeholders in the health care system in ways that allow for an understanding of how the findings relate to their practice. In addition, complex patient interactions can be analyzed in ways that make sense of patterns of relationships that occur across practitioners and patients to try to better understand complex medical decisions, such as the decision to have a major surgery or determining end-of-life care. In this way, we can work to bridge the gap between research into the practices of those in the health care system and the impact on areas such as medical training, shared decision making, and patient satisfaction, without losing our appreciation for the complexity of these environments.

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Workshops

Open Science and the Reproducible Open Coding Kit Workshop

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1 Overall Focus of Workshop

The aim of the workshop is two-fold: firstly, we will explore our own (and the greater community's) attitudes toward Open Science (OS) as applied to qualitative research; and secondly, we will walk through the fundamentals of the Reproducible Open Coding Kit (ROCK) with a special focus on how it can be employed for Quantitative Ethnographic (QE) analyses.

1.1 Open Science for Qualitative Research

The recent "credibility crisis" in psychology has made salient how many common research practices contribute to biased conclusions and prohibit inclusivity and accessibility of science. As a result, tools and practices that increase the credibility and accessibility of the scientific endeavor and its output have proliferated. However, these have often been geared towards studies using quantitative methods, still leaving much work to be done for researchers using qualitative methods. Those researchers may have diverse reservations about implementing OS standards and practices. For example, they may see difficulties in the ability to anonymize narratives, believe sensitive information prohibits anonymization, might consider hermeneutic processes impossible to make transparent, or may believe transparency is not helpful in improving the quality of their work. We believe it is important to bring arguments for and against OS to light and that the scientific community would benefit from such a discourse.

1.2 The Reproducible Open Coding Kit

The Reproducible Open Coding Kit (ROCK) is a standard and convention that enables transparent qualitative research. This standard is implemented in two Free/Libre Open Source Software applications: an R package (rock) and a graphical interface (iROCK). The ROCK helps researchers organize data sources, designate attributes to the providers of those data, code (and segment) narratives, as well as perform various analyses. In accordance with the ROCK standard, the R package allows making these steps explicit and transparent, thus improving transparency, inclusivity, and accessibility of research while minimizing research waste. Furthermore, the ROCK facilitates sharing coded qualitative data, enabling other researchers to reproduce the coding process, compare results, and collaborate by sharing or expanding the coding system.

1.3 The ROCK for Open Science

The ROCK specifies conventions for including codes and attributes in plain text files. This standard enables coding and reading qualitative data without the requirement of any software other than a plain text file editor. Furthermore, because no proprietary software is necessary, researchers retain complete control over the data they process. This means that they do not need to enter into data processing agreements with third parties if they work with identifiable data. Yet, if researchers work with anonymized data, because the data is stored in plain text files, it can be shared with other researchers, who can then easily (adapt and) re-run the analyses.

1.4 The ROCK as applied to Quantitative Ethnography

The ROCK can also be employed to prepare data for Epistemic Network Analysis (ENA) software. Code trees can be specified with the standard, and the graphical interface eases manual coding and segmentation. At the end of the coding process, sources can be downloaded and processed as a CSV file. This file can then be uploaded into the ENA webtool or processed further with the rENA package.

2 Who Would Benefit from the Workshop?

All are welcome at the workshop. The activities may be of more interest to researchers working with qualitative data manually, and looking for a system with which to code and segment their narratives. Also, we welcome researchers interested in the implementation of OS principles to qualitative research and developing functioning standards, methods, and tools.

Knowledge of or experience with R and R Studio is not a prerequisite for attendance, but if you would like to participate, we strongly suggest you download these and become somewhat familiar with them prior to the workshop. The same applies to a basic knowledge of qualitative research (e.g. coding, thematic analysis) – it is not required, but having some experience in these tasks is beneficial to getting the most out of workshop activities.

3 Schedule and Activities

This is a tentative schedule and may be subject to slight changes.

Timeframe	Task	Description
Pre-workshop	Open Science online asynchronous debate	-Participants will be asked to contribute their thoughts on the pros and cons of OS as applied to qualitative research -Comments posted on an online interface will provide our raw qualitative data for the workshop
Part 1	Introductions	-Get to know each other (and form small teams) -Get to know the ROCK (basic functionality and workflow) -Get to know the raw data and work on a coding structure
Part 2	Coding and Segmenting	Participants will learn to: -assign attributes to sources of data -code and segment raw data with iROCK
Short break		
Part 3	Analysis	Participants will learn to: -perform basic analyses with the ROCK (in groups) -prepare their data for use in ENA (collectively)
Part 4	Showcase and Wrap-up	-Teams will present their different analyses -In closing, we will discuss some challenges and benefits of using the ROCK

4 Expected Outcomes

Participants will gain insights into the pro and con arguments for OS principles in qualitative research, as well as attain familiarity with a standard and toolkit with which they can conduct qualitative research in an open and reproducible manner. Pertaining to QE specifically, participants will learn a method to prepare data for use in ENA manually.

5 Beyond ICQE20

As a continuation of the pre-workshop activity, exploring the challenges and benefits of OS in qualitative research will remain an objective post-workshop also. The process piloted at the ICQE20 will be reproduced at multiple sites thereafter, yielding more data on researcher attitudes towards OS. This will be a project any ICQE participant can join if they wish, helping the QE community, and more broadly qualitative researchers, shift their paradigm to ensure more transparent processes, more reliable findings, spur collaboration, and enrich science in general.

Social Media Data Scraping for Social Scientists

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Abstract. Far too often, social scientists find themselves choosing qualitative research methods to address their academic research due to the perceived complexity of computer programing. The suggested pre-conference workshop, led by Woodson Hobbs and Chen Huang, is intended to help conference attendees access social media data to use in Epistemic Network Analysis (ENA) through simple coding strategies and techniques. Using python and the Twitter API (https://developer.twitter.com/), this workshop will identify strategies to gain access to data with simple coding strategies. Additionally, the workshop will teach attendees how to use the Data Miner tool (https://data-miner.io/) to scrape Facebook data without needing access to Facebook's API.

Keywords: data scraping, epistemic network analysis, coding, API.

1 Introduction

1.1 Intended Audience

The intended audience for the Social Media Data Scraping workshop is for academics and researchers interested in evaluating discourse on social media sites, specifically Facebook and Twitter. Additionally, the coding and scraping techniques taught in this course can be used to access information outside of Facebook and Twitter and can be used for scraping Reddit, LinkedIn, as well as other text-based social media sites.

1.2 Presenter Biography

Woodson "Quinn" Hobbs is a social media and marketing consultant based in Playa del Rey, California. Also a Ph.D. student in Global Leadership in Change, Quinn specializes in social media data acquisition and analysis. A self-taught web-developer, Quinn's coding methodology is approachable for those with little to no computer literacy. Having consulted for multibillion-dollar corporations and small micro-agencies, his perspective on digital strategy is highly specialized to the end user's needs. Quinn's pedogeological approach centers around teaching self-efficacy in computer literacy through practical utilization of existing online training and resources.

Chianti Huang is currently a Ph.D. student in Global Leadership and Change at Pepperdine. Before her scholarly work, she was the co-founder of a female empowerment platform dedicated to promoting gender equality between China and the

United States. Currently, she is the chief curator of the well-known "Woman in Blockchain" and "AI, Crypto & Blockchain" conferences in South California.

2 Workshop Structure and Background

2.1 Primary Goal of the Workshop

The primary goal of the pre-conference workshop is to aid attendees with easy-to-understand programing training to gain access to data on Facebook and Twitter. A recent Pew Research report revealed that 52% of Americans use Facebook as a source of news, and 17% use Twitter [2]. With the ability for immediate human response on press releases via social media outlets, quantitative ethnography is an effective tool for evaluating modern human discourse. Thus, helping academics and researchers access this data in real-time is beneficial for study efficacy and reliability.

With the unfortunate COVID-19 pandemic, social media use has increased substantially and will continue as stay-at-home orders return to several states [4]. One challenge in qualitative ethnography is accessing relevant data to specific to social media networks. For example, in the 2020 QE Data Challenge [6], many teams struggled to find relevant data to their specific research question even with the myriads of existing data provided. With over 1.73 billion active daily users on Facebook [3], the relevancy of this data is essential not only for valuable for businesses but also for academics in evaluating the behaviors of social media discourse.

The ENA Tool [1] and nCoder [5] are excellent tools for developing networks built on social media conversations. To develop these networks with little to no coding experience quickly can be challenging, as Twitter and Facebook have daunting APIs. However, this workshop's goal is to create a repeatable and straightforward process for scrapping data such that it can be used with the nCoder [5] system and ENA Tool [1].

2.2 Workshop Schedule

Prior to Pre-conference workshop. Before the workshop, a request for submissions from other academics, who are similarly accessing the Facebook and Twitter APIs. Ideally, each user would create a short three-to-five-minute video of their process acquiring data and then deliver a short presentation explaining their intended application of ENA to their data. Additionally, a pre-conference tutorial on getting their computers (both Mac and PC compatible) for the conference will be provided via online training created by Woodson Hobbs and Chianti Huang.

Table 1. Schedule for Pre-Conference Workshop

Presenter	Topic
Chianti Huang	Introduction to Social Media Data and intended use for ENA
Compiled video of submissions for conference	Multiple examples of using Twitter and Facebook data for ENA research
Video Submitters	Q&As with Video Creators. As well as, questions regarding, what are potential uses for Twitter and Facebook data? Determine what the audience intended use for accessing data.
Woodson Hobbs	Introduction to Twitter API: How to scrape Twitter by #'s, Twitter ID, and by Tweet
Chianti Huang	Individual Q&A / Breaktime
Woodson Hobbs	Scraping Facebook and other sources using Data Miner Application.

2.3 Workshop Outcomes and Follow Up

Attendees at the pre-conference workshop will be able to access the Twitter API and extract data for their academic research. Additionally, each attendee will have a better understanding of the Data Miner tool and how to extract data from existing websites like Facebook effectively.

Following the workshop, ideally, there would be a QE Society approved online forum for academics and researchers engaged in social analytics for ENA research. The forum would be a resource for individuals to look up Python scripts, and R-Code scripts pertaining to social media ENA. Additionally, forum subscribers could use the forum to find existing datasets to be used for their research.

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Introduction to Epistemic Network Analysis (ENA)

Kamila Misiejuk, Clare Porter, 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.

Advanced ENA Interpretations

David Williamson Shaffer, Amanda Barany, and Yeyu Wang

This advanced workshop on interpreting Epistemic Network Analysis (ENA) models introduces participants to key issues with interpretation of ENA dimensions, network features, and statistical results. Participants learn about key elements of ENA mathematics, with an emphasis on rotation and dimensional reduction; explore how ENA results are visualized as two coordinated representations in a single metric space; and gain a deeper understanding of how to analyze and refine ENA models.

Introduction to nCoder

Amanda Siebert-Evenstone, Seung B. Lee, and Brendan Eagan

This workshop will introduce methods for valid and reliable automated coding of text data using the nCoder webtool and R package. 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 and rENA

Zachari Swiecki, Vita Kovanovic, and Yeyu Wang

In this workshop, we will introduce participants to advanced features of epistemic network analysis (ENA) available in the webtool and the rENA package for R, including weighted models, projection, masking, and trajectories. Participants will work in groups to apply these features on one of several sample datasets. Our emphasis 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.

Keynotes

Human Factors ad Quantitative Ethnography: Exploring Interactions to Improve Systems

Abigail R. Wooldridge

Department of Industrial and Enterprise Systems Engineering
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Human Factors and Ergonomics (HF/E) is the scientific discipline concerned with understanding and designing the interactions between humans and systems to optimize human well-being and overall system performance. While quantitative ethnography (QE) originated and continues to thrive in the learning sciences, HF/E is an example of one field that has begun to successfully adopt quantitative ethnography techniques. During this talk, we will briefly explore HF/E as a field and examples of QE in HF/E. We will focus on how and why QE helped to gain a deeper understanding of the sociotechnical system in health care settings. Further, we will consider how to continue to leverage QE in HF/E; implications and considerations for introducing QE in new fields will also be discussed.

Quantitative Ethnography Visualizations as Tools for Thinking

Simon Buckingham Shum

Professor of Learning Informatics
University of Technology Sydney

All research must give form to data and insights. Visualizations serve as cognitive extensions that assist researchers not only in exploring their data, but in communicating findings to colleagues and broader audiences. Especially in data-intensive fields, widely used software tools define, and are defined by, research communities; you can't fully participate in a community until you can wield its tools responsibly. In an emerging field like Quantitative Ethnography (QE), inventing its own tools, how we model and map the world are therefore defining characteristics, and merit critical reflection.

QE's principles currently find fullest expression in Epistemic Network Analysis (ENA). It's fair to say that the interest in ENA is attributable not only to the power of its data modelling and analysis, but also to the engaging, interactive visualizations it generates. Inspired by the ways I see ENA used, in this talk I bring my background in Human-Computer Interaction and the design of tools for working with conceptual structures, as a lens on ENA and other QE-generated visuals. When we consider in detail how external representations serve as personal and shared cognitive tools, this illuminates current and future techniques for presenting QE analyses. A data-storytelling lens asks how the audience will engage with our insights, while participatory methods ask whether we cast them as passive recipients or active agents in validating those narratives. Moreover, as QE analyses begin to underpin new tools designed for people other than QE researchers, human-centred design should give voice to non-technical stakeholders. These lenses could point to a future in which visualization tools evolve to scaffold more participatory forms of sensemaking as an important hallmark of how QE models and narrates the world.

Special Session

Future of Quantitative Ethnography: Promises and Challenges

Mamta Shah, Marta Jackowska, Amanda Barany, Marcia Moraes, Zachari Swiecki, and Szilvia Zörgő

As the Quantitative Ethnography (QE) community matures, it is important to engage in active discussions on emergent themes and the evolution of the field. This 60-minute special event at ICQE20 will involve a semi-structured interactive fireside chat with 4 QE scholars. The broad focus of this event is to facilitate a discussion on challenges QE scholars experience, strategies to overcome them, and what opportunities QE presents to us in advancing research and practice. The panel consists of early career scholars using QE in diverse domains. As the co-chairs of this event, Dr. Mamta Shah (Learning Scientist, Elsevier) and Marta Jackowska (Ph.D. Candidate, Aarhus University) will moderate a discussion on how the invited panel positions themselves as QE scholars, what questions are being explored via QE in their respective domains, which QE techniques are being applied (or not, but should be), and what recommendations the panel has on helping scholars strengthen their knowledge and skills pertaining to QE. The event is also designed to include time and space for the audience to ask questions and share their reflections on the aforementioned topics. We believe this special event will resonate with a wider audience in the QE community.