Is QE Just ENA?

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Abstract. In the emerging field of quantitative ethnography (QE), epistemic network analysis (ENA) has featured prominently, to the point where multiple scholars in the QE community have asked some variation on the question: *Is QE just ENA*? This paper is an attempt to address this question systematically. We review arguments that QE should be considered a background and justification for using ENA as well as arguments that ENA should be considered merely one approach to implementing QE ideas. We conclude that ENA is used in QE, but not exclusively; and that QE uses ENA, but not exclusively; but that the answer to this question is less important than the reflexive thinking about methodology that has been a key focus of the QE community. Our hope is that, rather than a definitive answer to this question, this paper provides some ways to think about the relationships between theory, methods, and analytic techniques as the QE community continues to grow.

Keywords: Epistemic Network Analysis · ENA · Quantitative Ethnography · QE · Data Philosophy

1 Introduction

For the *Second International Conference on Quantitative Ethnography* (ICQE20), Porter et al. [39] conducted a systematic review of the literature from the field of *quantitative ethnography* (QE) and reported that "QE was often only discussed as a methodological framework from which ENA emerged." Indeed, walking into the poster session at ICQE19 looked like a veritable sea of *epistemic network analysis* (ENA) diagrams: 14 out of 25 (56%) of posters at ICQE19 used ENA.

By that metric, the predominance of ENA in the QE community has continued and even increased. ENA was used in 9 of 15 posters (60%) at ICQE20 and 17 of 19 posters (89%) at ICQE21. Thus, while QE studies have used other statistical and machine learning techniques—including process mining, quantitative multimodal interaction analysis, and non-negative matrix factorization [39]—it is easy to see why an undercurrent of discussions within the QE community asks about the relationship between QE and ENA.

This paper is an attempt to address this issue systematically. We review possible arguments that QE should be considered a background and justification

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for using ENA as well as arguments that ENA should be considered merely one approach to implementing QE ideas. (We also discuss reasons why the answers to these questions might not actually matter.)

So as not to be coy, let us state from the outset that based on these arguments, we think that neither view is correct: ENA is used in QE, but not exclusively; and QE uses ENA, but not exclusively. Of course, we do not anticipate that this overview will provide a definitive answer to the question—nor do we believe it should, as reflexive thinking on research methods is one of the hallmarks of a healthy community. Rather, our hope is to provide a framework that might make such discussions more productive as the community grows.

2 QE Is Just ENA

2.1 Argument from History

The past is never dead.
—William Faulkner, *Requiem for a Nun*

The application of statistics in qualitative research has a long history. It has been particularly prominent in the domain of interrater reliability measures [13], which are used to warrant the validity and reliability of coding schemes.

The earliest references to "quantitative ethnography" in Google Scholar are from the 1980 s, primarily in the work of Kleinman [26]. Building on a longer tradition of quantitative methods in ethnographic research (e.g., [12]), Kleinman argued that quantitative ethnography was a collection of "scaling techniques, ethnoscientific eliciting frames, sociolinguistic instruments, and measurement of time, space, change, and other coordinates of behavior and communication" which, when combined with qualitative data, "can be a standardized research method for assessing validity." Studies using this approach typically either counted the frequency with which themes appeared in interviews (see, e.g., [25]) or computed linguistic features of talk, such as measures of cohesion or linguistic complexity (see, e.g., [33]) that described the structure of talk but not its content.

In 1996, Bernard [6] described in general terms the process of using quantitative techniques on "qualitative data," including an argument that sounds strikingly similar to one of the core tenets of QE as it is used at ICQE:[1]

> It's tempting to think that qualitative analysis of text ... keeps you somehow "close to the data." When you do qualitative analysis of a text, you interpret it. You focus on and name themes and tell the story, as you see it, of how the themes got into the text in the first place.... In any event,

[1] Bernard also argued for the qualitative examination of quantitative data, again sounding strikingly similar to more recent arguments. He claims that qualitative analysis of quantitative data is "the search for, and the presentation of, meaning in the results of quantitative data processing." He argues that without such work, quantitative studies are "puerile."

> you have to talk about the text, which means you have to produce labels for themes and labels for articulations between themes. All this gets you away from the data, surely as numerical coding does. Quantitative analysis involves reducing people (as observed directly or through their texts) to numbers, while qualitative analysis involves reducing people to words.

However, while this description of the quantitative analysis of qualitative data is consistent with QE research, neither Bernard nor his predecessors or contemporaries problematized the nature of the warrants that result from such work.

In 2004, Shaffer and Serlin [46] proposed *intrasample statistical analysis* as an approach to unifying qualitative and quantitative methods. Shaffer and Serlin argued that if individual students (or units of analysis more generally) were included as *fixed effects* in a statistical model, then a statistical analysis of events in thick data of the kind qualitative researchers use would generalize *within* the data.[2] That is, statistical measures could warrant *theoretical saturation* of qualitative analyses. As described in Shaffer [42], this statistical claim became the foundation of QE as a research method. However, Shaffer and Serlin (as well as Bernard and others) did not address a second fundamental question in QE research: namely, how to organize thick data of the kind that qualitative researchers typically use to make such statistical analyses possible.

Building on nearly a decade of research in the Learning Sciences, the question of organizing and quantifying thick data was addressed in detail by Chi [11], and it is on this framework that ENA was developed. More specifically, ENA combined Chi's organizational framework with *epistemic frame theory* [40], which was itself influenced by and extended theories of *situated* and *information-processing* views of cognition (see, e.g., [14,28]).

According to epistemic frame theory, complex thinking skills are developed (and deployed) in the context of specific *communities of practice*. These communities, in turn, have cultures of practice that consist of the skills, knowledge, values, identities, and epistemologies that members of the community use to ask and answer questions and solve problems. Critically, however, epistemic frame theory argues that becoming enculturated into a community of practice meant understanding how these cultural elements were systematically *connected* to one another. Originally—and up to 2011 (see [4])—epistemic frames were analyzed qualitatively to document these connections.

The first reference to ENA itself is a paper from 2009 by Shaffer et al. [44]. The paper describes ENA by suggesting that a network is an appropriate way to model the connections among skills, knowledge, values, identities and epistemologies in a culture. Specifically, Shaffer et al. proposed (a) coding turns of talk (or chat messages) in data and (b) constructing a network model based on

[2] Technically, Shaffer and Serlin argued that such a statistical analysis would generalize to a *hypothetical sample* taken from "all the things that we might have recorded about these students in the given context from a particular perspective." Thus, statistical significance meant that the analysis was *saturated* in the sense that the results generalize to other possible data that might have been collected or examined under the original circumstances.

the co-occurrence of codes within a *strip* of activity—borrowing the notion of strips of activity from Goffman [21].

At this stage, there was no concept of a window (moving or otherwise), and the network representations and analyses drew on the existing tools of social network analysis, including non-deterministic Kamada-Kawai spring mass models analyzed using weighted density and relative centrality (see Fig. 1).

Between 2009 and 2018, new mathematical and graphical representations were proposed for analyzing epistemic frames, all of which were described as forms of ENA. For example, Hatfield and Shaffer proposed an *integration-cohesion index* for codes . Both *dimensional reduction* of network adjacency matrices [3] and *co-registration of network graphs and plotted points* [35] were proposed in 2012, as well as an impossible-to-read three-dimensional version of such a projection [36] (see Fig. 2). In 2014, Borden et al. released the first ENA Webkit [7], which introduced the scheme for displaying line weights that is used in the current ENA tools (see [48]). *Moving stanza windows* were proposed in 2016 [47], and were incorporated into a second version of the ENA Webkit [31] and rENA package [30] in 2018—the same year in which nCoder, first proposed in 2015 [43], was released as a web tool [32].

It was during this mathematical and conceptual development of ENA in 2015–2017 that *Quantitative Ethnography* [42] was written. *Quantitative Ethnography* was the first description of QE and first use of the term (as this community uses it) in print, although it had been used at conferences and in presentations earlier (see, e.g., [41]). Notably, the book is organized so as to lead up to ENA as the final expression of QE, and it is the topic of the penultimate chapter.

The development of QE and ENA were thus deeply intertwined. This history of co-development and co-presentation suggests that QE and ENA are on a very deep level inseparably connected.

2.2 Argument from Authorship

Every invention was once just a thought inside someone's head.

—William Federer, *Change to Chains*

As is more or less clear in this historical account of the development of QE and ENA, both of these contributions were developed by a single, relatively small group of researchers at the University of Wisconsin–Madison. Indeed, one criticism of QE is that the community is still dominated by work located in one research group [16]. The first QE conference (ICQE19) was in Madison, Wisconsin, and at the most recent conference (ICQE21), 13 out of 27 (48%) full papers had at least one person affiliated (concurrently or previously) with the University of Wisconsin–Madison. While it is true that the Epistemic Analytics Lab (the developers of QE and ENA) have developed tools other than ENA—nCoder [32] being only the most notable—in the years since the publication of *Quantitative Ethnography*, 39 out of 48 (81%) publications about QE from the lab have been related to ENA.

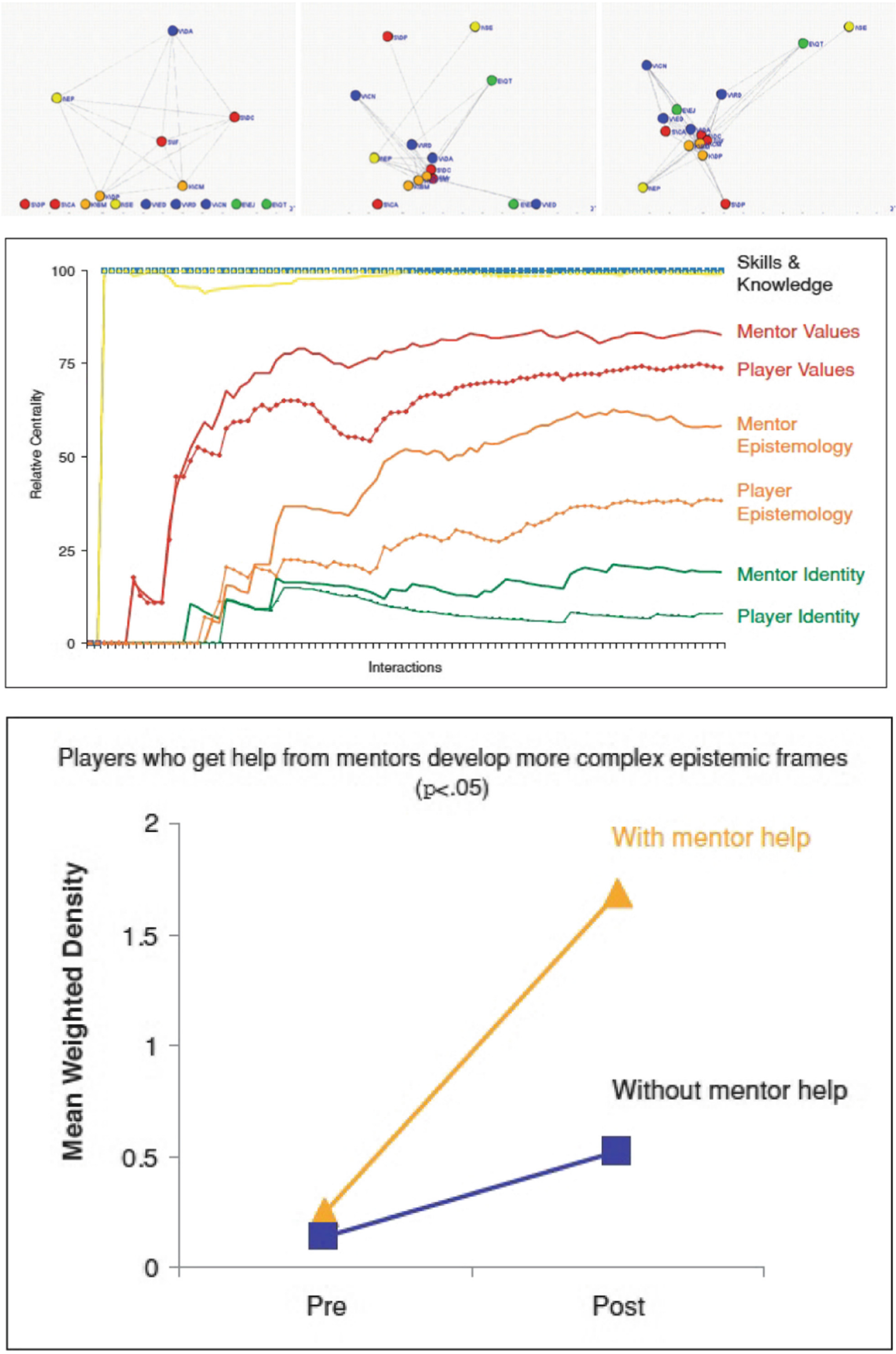


Fig. 1. Traditional network visualizations and summary statistics from the first paper on ENA.

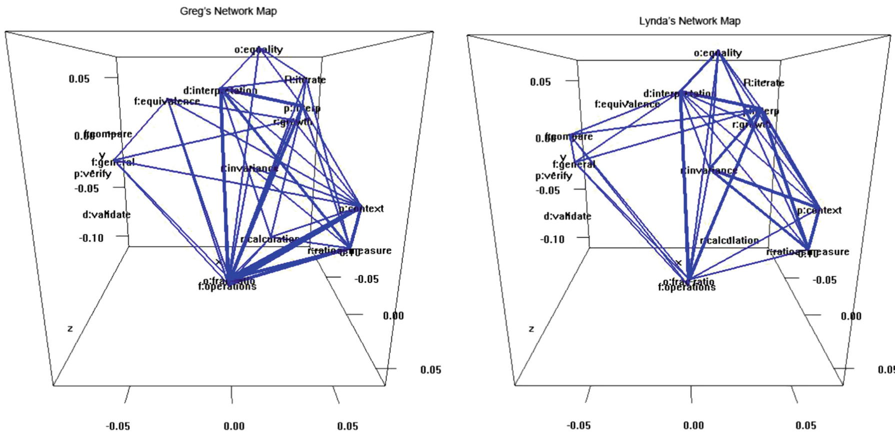


Fig. 2. A misguided attempt to construct three-dimensional ENA models (2013).

In other words, QE and ENA were both created at the University of Wisconsin–Madison. Researchers from the Univeristy of Wisconsin–Madison are involved in a large portion of papers published in and by the QE community. And an overwhelming proportion of QE papers from the University of Wisconsin–Madison involve ENA. Thus, the shared authorship of QE and ENA and the continuing presence of those authors in the QE community suggest that the distinction between QE and ENA may be small.

2.3 Argument from Usage

If you want to understand what a science is, you should look in the first instance not at its theories or its findings, and certainly not at what its apologists say about it; you should look at what the practitioners of it do.
—Clifford Geertz, *Thick Description*

Stupid is as stupid does.
—Mrs. Gump, *Forrest Gump*

As the statistics above show, what the practitioners of QE primarily do is ... ENA. But in addition to the historical and personal (or personnel) reasons above, ENA is a useful tool for QE researchers due to its alignment with QE practices.

In general, QE suggests that models should be *fair samples* in the sense that Goodman [22] describes. For Goodman, a fair sample is “one that may be rightly projected to the pattern or mixture or other relevant feature of the whole or of further samples” (p. 135). As an example, Goodman describes swatches from a bolt of cloth, arguing that some swatches would give a more accurate picture than others of the pattern that could be seen in the cloth as a whole. The most fair swatch is the one that gives us the most information about what we might expect to see in future swatches.

Shaffer and Ruis [45] (building on Shaffer [42]) describe four key forms of *QE fairness*:[3]

1. **Fairness to theory**: The methods used are a good reflection of the constructs used in the theories to which they relate—that is, a proponent of a theory would agree that the methods are aligned with it.
2. **Fairness to community**: The methods used are a good representation of the *emic perspective* of the community being studied—that is, a member of the community would agree that the methods are consistent with the cultural norms and meanings of the community.
3. **Fairness to data**: The methods used are a good model of the data and its structure—that is, relevant features or parts of the data are not omitted.
4. **Fairness to subgroups**: The methods used are equally fair to any relevant subgroups within the theory, community, or data—that is, there are not certain ideas, groups of people, or subsets of the data that are treated differently in some inappropriate way.

Shaffer and Ruis discuss these questions of QE fairness in the context of coding data: for example, the role of a clear code definition or inter-rater reliability measures in developing fair classifiers. However, these principles of QE fairness clearly apply to all aspects of QE work, including the models that are constructed using fair codes.

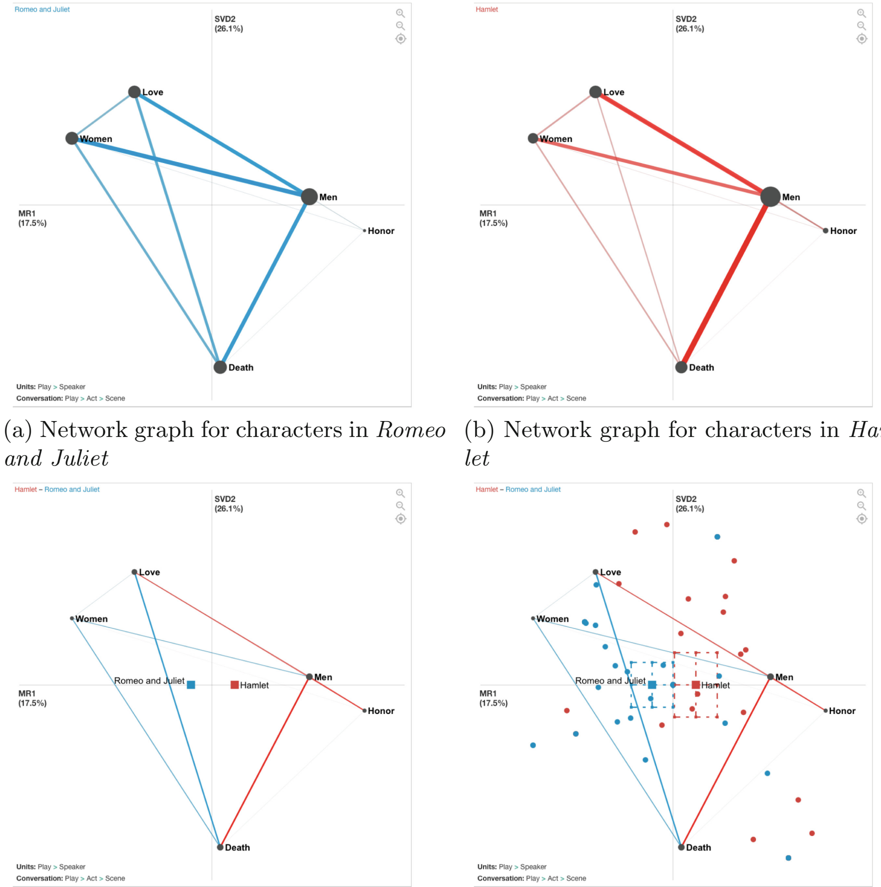
In this regard, ENA has specific affordances for creating fair QE models.

ENA Models Are Perceptual. Li [29] argues that effective data visualizations use *preattentive processing*: that is, they take advantage of low-level visual processing that takes place before conscious awareness to help viewers rapidly and accurately interpret an image.

The graphic design features of ENA network graphs are described elsewhere [48], but briefly, these graphs use a combination of color, saturation, size, and position that help viewers rapidly interpret the graphs. Specifically, ENA represents [C]odes as *nodes* with size proportional to their overall connection strength in the model, and connections between [C]odes as *edges* with thickness and saturation proportional to the strength of the connection. The result is to create a gestalt shape that has weight distributed across the connections.

Although reading any visualization requires a degree of *recognizability*, or the ability to identify features based on previous encounters [29]—ENA graphs make it relatively easy to identify influential codes (they are larger and have more connections coming into them) and influential connections (they are thicker and darker) in a model (see Fig. 3a).

[3] Shaffer and Ruis present three forms of fairness (theory, community, and data) together and then discusses subgroup fairness separately. However, we believe it is conceptually clearer to think of four co-equal criteria for fairness. We also note that these criteria do not explicitly reference ethical issues in theory (such as plagiarism), interactions with a community (such as informed consent), data (such as p-hacking), and subgroups (such as unconscious bias). However, we take these as shared assumptions about acceptable research practices.



(a) Network graph for characters in *Romeo and Juliet*

(b) Network graph for characters in *Hamlet*

(c) Subtraction plot comparing characters in *Romeo and Juliet* and *Hamlet*

(d) Plotted points comparing characters in *Romeo and Juliet* and *Hamlet*

Fig. 3. ENA visualizations and data representations

ENA Models Are Consistent. The general problem of determining whether two network graphs are equivalent cannot be solved algorithmically [37]. However, it is possible to visually compare network graphs with high accuracy if their nodes are positioned isomorphically [23].

ENA uses a mathematical algorithm, specifically a dimensional reduction technique followed by an optimization, to position the nodes of its network graphs (see [8] for details). As a result, the positions of the nodes are *graph invariate*, which facilitates visual comparison of networks. For example, because the nodes in Figs. 3a (*Romeo and Juliet*) and 3b (*Hamlet*) are isomorphic, we can easily see that the connection between MEN and HONOR is stronger in *Hamlet* than in *Romeo and Juliet*, while the connection between LOVE and DEATH is stronger in *Romeo and Juliet* than in *Hamlet*—neither of which will surprise readers familiar with the plays.

ENA Models Are Interpretable. As a result, the differences between ENA models can be interpreted not just in terms of the differences in the *structure* of the networks (for example, which network is more densely connected, or which network has more central nodes) but based on their *content*—that is, which specific nodes are more or less strongly connected.

Thus, while both *Hamlet* and *Romeo and Juliet* are about LOVE and DEATH, by subtracting their networks (see Fig. 3c), we can see that these themes are more strongly connected to MEN in *Hamlet* and more strongly to WOMEN in *Romeo and Juliet*—again, not a surprise to those who know the plays.

Because the positions of the nodes are graph invariate, the *centroids* of the graphs can also be compared. The centroid is the weighted average of the connection strength of each node—which corresponds to the point where the connections in the graph balance left-to-right and top-to-bottom. Thus, the centroid of *Romeo and Juliet* (shown by the red square in Fig. 3c) is to the left of the centroid for *Hamlet* (the blue square) because the connections in *Romeo and Juliet* are stronger between the codes on the left side of the network graph and the connections in *Hamlet* are stronger on the right.

ENA Models Are Scalable. ENA's dimensional reduction technique represents each network with a *plotted point* (often referred to as an *ENA score*). The algorithm positions the nodes in space such that the centroid of each network *approximates* the location of the network's plotted point. Each network is thus represented by a point that is *co-registered* with its associated network graph.

This co-registration means that the networks are embedded in a space whose *dimensions* can be interpreted. Networks whose points have higher x coordinates make more connections to nodes on the right side of the space. Networks whose points have lower y coordinates make more connections to nodes in the lower part of the space. And so on.

As a result it is possible to compare very large numbers of networks statistically based on the locations of their points in the space, and to interpret those statistical differences using their co-registered network graphs. For example, Fig. 3d shows a comparison of characters in *Romeo and Juliet* and *Hamlet*. The points represent a network for each character. The mean networks are compared using a *t-test* and the difference can be interpreted using the subtracted network graphs of the means.

ENA Models Are Transparent. Critically, however, although ENA models are mathematically complex, they are not black boxes. It is possible to look at the edge of any network in the model and see the parts of the underlying data that generated the connections being modeled. Thus, it is possible to *close the interpretive loop* [42] and ground the results of the complex model in the original data.

As a result of these affordances, ENA models provide a continuous chain of co-registered representations: interpretations of a model can be linked to the dimensions of the ENA space, which are determined by specific plotted points in the model, which can be interpreted in terms of their associated network graphs, which are determined by—and can be linked back to—the original data. This chain of representations, in turn, makes ENA models open to inspection in terms of their fairness to theory, community, data, and subgroups. As a result, ENA exemplifies QE principles of fairness in modeling connections in [d]iscourse, which is the basis for inferences about the [D]iscourse of a community.[4]

In other words, the structure of ENA emerges from and exemplifies key concepts in QE. It is thus no surprise that *Quantitative Ethnography* describes steps in manipulating data that lead to ENA—and no surprise that ENA is the most prominent technique in QE research. The two are inextricably linked.

3 QE Is Not Just ENA

Having examined some of the strongest arguments that QE and ENA are linked in such a way that it is impossible to do QE without doing ENA (and vice versa), we now turn to arguments that QE and ENA should be though of as distinct, albeit related, approaches to data analysis.

3.1 Argument from Symbolic Logic

[T]he proposition "All X is Y" is interpreted to mean that there is no such class of things in existence as "X that is not-Y."

—John Venn, *On the Diagrammatic and Mechanical Representation of Propositions and Reasonings*

The most obvious problem with asserting that all QE is ENA is that it is logically inconsistent. If 14 out of 25 (56%) posters at ICQE19 used ENA, then it is equally true that 11 out of 25 posters (44%) did *not* use ENA. Similarly, if in the years since the publication of *Quantitative Ethnography*, 39 out of 48 (81%) of the publications about QE from the Epistemic Analytics Lab in Madison have been related to ENA, then 9 out of 48 (19%) have not been about ENA.

On one hand, tools exist (or are being developed) that have been used or can be used in QE studies that do not involve ENA: for example, ROCK [38], nCoder [32], ordered network analysis (Tan et al., this volume), network trajectory analysis [9], transmodal analysis [27], Quick Red Fox [24], process mining [34], quantitative multimodal interaction analysis [1], multimodal matrices [10], and non-negative matrix factorization [5]. Moreover, many of these tools were not developed at the University of Wisconsin–Madison or even with QE originally in mind.

[4] The use of capitalization denotes the difference between events in the world ([l]ower case) and claims about a culture ([U]pper case). This terminology comes from Gee [18] and Shaffer [45].

On the other hand, studies have used ENA without applying any of the theoretical machinery of QE. For example, Andrist et al. [2] used ENA to model the extent to which two people were looking at the same things during interactions documented in eye-tracking data.

The issue is that ENA is a method for producing perceptual, consistent, interpretable, scalable, and transparent network models. But as a mathematical modeling technique, it is agnostic as to the type of data, its source, or the chain of evidence that preceded the ENA model. Ultimately, ENA requires nothing more than a matrix of codes and associated metadata as parameters to the model.

QE, on the other hand, requires attention to the types and sources of data and the chain of evidence that precedes any model. QE studies thus highlight:

1. **Reflexive data collection.** QE researchers follow principles of good qualitative research, particularly with regards to ethical collection of data that provides a fair representation of the individuals and/or community being studied—recognizing, of course, that any study is an interaction between researcher and participants, and thus the researcher's own perspective and its impact needs to be taken into account [20].
2. **Grounded analysis.** QE researchers follow principles of good qualitative research to develop thick descriptions of the contexts from which their data comes, focusing on questions of why and how some specific people in some specific setting acted as they did. Critically, this includes developing familiarity with the data to the point where a claim is based on a theoretically-saturated interpretation of the context—recognizing, of course, that there are always multiple possible interpretations of a context being studied [19].
3. **Meaningful segmentation.** QE researchers construct qualitative data tables that operationalize the structure of their data based on a theory or theories of discourse rather than using arbitrary boundaries between segments of data [49]. Moreover, such segmentation has to provide lines of data that can be considered exchangeable for the purpose of quantification—that is, lines of data that can be meaningfully counted [42].
4. **Fair and valid coding.** QE researchers classify data based on a grounded understanding of the context, choosing [C]odes that are meaningful in the [D]iscourse in that setting and that can be used to explain that [D]iscourse in terms of the relationships among those [C]odes in the setting [42]. In operationalizing these [C]odes, they attempt to fairly represent the theoretical constructs, data, and community from whom the data was collected using methods whose reliability and validity can be systematically assessed. Because any classification method will produce some error in the resulting [c]odes, QE researchers strive to ensure fairness by using classifiers with very high levels of reliabililty [45].
5. **Interpretable and transparent models.** QE researchers construct models based on fair codes whose results can be interpreted meaningfully because they align a quantitative model with a grounded analysis. They construct models that make it possible to inspect all of the components of the model, and identify segments of data (and combinations of segments) that produce

specific model outcomes—and while recognizing that all models are inexact, they strive to ensure fairness through a process of *closing the interpretive loop*, or testing the validity of a model by qualitatively inspecting the data in light of the model that was produced.

In other words, QE is an approach to data analysis designed to warrant theoretical saturation of qualitative analyses using quantitative techniques. Because of its affordances, ENA is a particularly useful tool for conducting QE research. But the principles and practices of QE in no way constrain researchers to use ENA. Similarly, although ENA is a particularly useful tool for QE research, ENA can be used without reference to the principles and practices of QE.

3.2 Argument from the Nomenclature

Rose is a rose is a rose is a rose.
—Gertrude Stein, *Geography and Plays*

Adding to the conflation of QE and ENA has been an unfortunate tendency for people in the QE community to describe any network modeling tool used in QE as some form of ENA—for example, Threaded ENA, Directed ENA, or Trajectory ENA—including, in many cases, the developers of such tools.

One way to think about ENA is as a tool that accumulates co-occurrences of codes in data, performs a mathematical manipulation of the resulting matrices, and then displays the results using a network graph. The problem with viewing ENA at this level of generality is that by this definition, almost any network analysis tool could be considered a version of ENA.

Alternatively, one could think of ENA as a tool that accumulates co-occurrences of codes in data *using a particular algorithm*, performs a *specific mathematical manipulation*, and displays the results using *one form of network graph.*

By this more restricted definition, many of the tools that the community refers to as some flavor of ENA bear no more resemblance to the original ENA than the original ship of Theseus did to the ship after it was preserved by the Athenians.[5] For example, ordered network analysis (Tan et al., this volume)—a tool that uses different methods for accumulation, dimensional reduction, and visualization than ENA—should be considered a different tool, and to the extent that it is used in QE work, would provide another example of the separability of QE and ENA.

A more tenable view is perhaps somewhere in between, taking a core component of ENA as the concept of co-registration of network graphs and dimensional reduction. But even under this intermediate definition it is not clear whether QE appears to be equivalent to ENA based on their conceptual integration or because of a poor choice of naming convention.

[5] The Ship of Theseus is a paradox raised by Heraclitus of Ephesus (and others, including Thomas Hobbes) asking whether an object that had all of its parts replaced was still the same object.

4 Does It Matter?

In the preceding sections, we have attempted to articulate what seem to be the key arguments regarding the ontological status of QE and ENA. We argue that although QE and ENA share a common history and original authorship—and despite the large number of QE studies that use ENA—they should be considered as related but separable approaches to data analysis. There are QE studies that do not use ENA, and ENA studies that do not use QE. Rather, ENA is a particularly useful tool for enacting QE principles, but the principles of QE and the processes of ENA are distinct.

It is eminently possible to do (1) reflexive data collection, (2) grounded analysis, (3) meaningful segmentation, (4) fair and valid coding, and (5) construction of interpretable and transparent models to (6) close the interpretive loop and (7) warrant theoretical saturation using quantitative techniques—all without using ENA. Similarly, researchers have used models that rely on affordances that are (a) perceptual, (b) consistent, (c) interpretable, (d) scalable, and (e) transparent—without any reference to QE principles or practices.

In making these arguments, however, we recognize that the primary concern of scholars asking about the relationship may not be whether or not the two techniques are separable or not. Rather, we suspect, the concern is about the dominance and influence of this one tool (and by extension those who developed it) on the QE community and its work.

But we argue that the development of new fields often unfolds this way. For example, the field of *minimally invasive surgery* largely developed around a specific set of technologies, namely the *endoscope* and surgical tools that could be inserted through very small perforations in the skin, such as catheters and laparoscopic scissors. But minimally invasive surgery, though in many contexts used interchangeably with endoscopic procedures, is a theoretical perspective that surgical interventions should minimize tissue damage to accelerate postoperative recovery, lessen pain, and reduce the risk of complications and infection. Although most minimally invasive procedures, beginning in the 1980 s, consisted of some form of real-time moving imaging combined with keyhole or percutaneous tools operated manually, the field has since evolved to include a range of computer- and robot-assisted procedures, among other technical advances [17].

More generally, as Darden [15] argues, new fields of study emerge when a new scientific technique makes it possible to observe or construct something that, in turn, makes it possible to provide new solutions to old problems. This approach is generalized into a new theory, giving rise to new lines of research. In the case of QE, we suggest that the technique of ENA facilitated the construction of statistical models of grounded claims. This, in turn, made it possible to describe a more general approach to warranting theoretical saturation of qualitative analyses using quantitative techniques, which has led to the growth of the QE community.

But as with the example of endoscopy, despite the importance of some initial technique, a field expands on its origins rather than remains beholden to them—although it may be too soon to expect this process to have fully matured in a community that is only holding its fourth annual conference.

We conclude, therefore, that the question of the relationship between QE and ENA is important to keep in mind as we move forward. However, there are sound theoretical and practical advantages to recognizing that QE and ENA are two different, though related, ways of analyzing data.

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