**Research Article**

**Network Mapping Methods for Qualitative Data: Application & Comparison of Two Social Network Mapping Protocols**

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# Abstract

**Introduction:** Mixed methods and qualitative analyses offer valuable insights by capturing the complexity and depth of human experience. However, these studies can be relatively subjective and challenging to convey visually. This study explores the use of network mapping tools, Kumu and Python, to provide visual representations of qualitative data analysis findings. **Methods:** We applied two different network mapping protocols, Kumu and Python, to a previous qualitative analysis of expert perceptions on environmental factors contributing to binge eating disorder. Kumu, an online platform, and Python, a versatile programming language, were used to create network maps that visualize the relationships between identified themes. The themes and subthemes from the original study were entered into Kumu and Python as mapping entities, and network maps were generated to compare the strengths and limitations of each approach. **Results:** Both Kumu and Python effectively visualized the relationships between themes identified in the original study. The Kumu network map highlighted the centrality of themes such as invalidation and invalidating environments, systemic issues and systems of oppression, and marginalized and under-represented populations. The Python-generated network map provided a similar visual representation with more detailed customization of visual parameters. **Discussion:** The use of network mapping approaches in this study provided valuable visual representations of the relationships between themes. Kumu’s user-friendly interface made it accessible for users with limited technical skills, while Python’s extensive library ecosystem allowed for more detailed and precise customization. The choice between the two approaches may depend on the specific needs and technical expertise of the user. **Conclusion:** Network mapping tools, Kumu and Python, offer innovative methods for visualizing qualitative data analysis findings. These tools enhance the understanding of complex relationships between themes and can inform the development of targeted interventions and policies. Future research should continue to explore the use of network mapping tools to further enhance qualitative data visualization and analysis.

**Keywords:** Network Mapping, Kumu, Python, Mixed Methods, Mixed-Methods, Qualitative Analysis, Biostatistical Modeling, Statistical Modeling, Binge Eating Disorder, Eating Disorder

**Abbreviations**: BED, binge eating disorder; DSM, diagnostic statistical manual; ED, eating disorder; GNN, graph neural network; GPUs, Graphics Processing Units; NumPy, Numerical Python.

# Introduction

Mixed methods and qualitative analyses offer valuable insights by capturing the complexity and depth of human experience [1-5]. However, these types of studies can be relatively subjective, even when conducted methodically [2,4,5]. Additionally, qualitative data findings can be challenging to convey visually, and it can be difficult to understand the relationships between identified themes [1].

In many fields, correlation matrices and network mapping tools are used to create visual representations of complex and interconnected data that inform analyses and inspire further research work. For example, in neuroscience, advanced imaging techniques are often paired with machine learning algorithms and specialized software (e.g., Graph Neural Networks (GNN), EdgeMap, DNNBrain) to create detailed neural network maps that explore how neurons interact within neural circuits and inform a better understanding of brain function and behavior [6-10]. In public health, sociology, business, and healthcare, surveys, interviews, and other data mining methods are often paired with methodological tools (e.g., Gephi, NodeXL, UCINET) to create social network maps that depict relationships and interactions between individuals or entities within networks to better understand social structures, identify key influencers, and study the flow of information and resources within networks [11,12].

Here, we used two different network mapping software and techniques – Kumu (<https://kumu.io/>, CA, USA) and Python (<https://www.python.org/>, VA, USA) – to develop two different network mapping protocols that can provide visual representations of qualitative data analysis findings.

**Kumu** is an online platform for visualizing complex systems through interactive network maps and diagrams. It is particularly useful for researchers and clinicians in social science fields like psychology, as it can facilitate detailed visual representations of relationships and patterns within data sets. Kumu blends systems thinking, stakeholder mapping, and social network analysis, making it accessible for users who may not have advanced technical skills but need to analyze and communicate complex information effectively.

**Python** is a versatile programming language widely used in various scientific and mathematical fields such as computational biology, statistics, and information technology and more recently in social and health science areas such as psychology and clinical health research. It is a language for managing large datasets and performing complex analyses [13-16] and its popularity stems from its simplicity, readability, and extensive ecosystem of libraries and documentation. For example, Python’s data science stack includes a collection of libraries and tools that are commonly used for data analysis, manipulation, visualization, and machine learning. These include **Numerical Python (NumPy**, a computational science library that supports large multi-dimensional arrays with a large collection of operational mathematical functions) [17], **Pandas** (a library that offers operations for efficient data manipulation and analysis through a spreadsheet-like 2-dimensional data structure known as a DataFrame) [18,19], and **Matplotlib** (a library for creating static, animated, and interactive visualizations) [20].

In addition to its data science stack, Python also has several libraries and tools for network mapping, both for a broader use and more specifically for neural and social network mapping. Of these, **NetworkX** is a key library that facilitates the creation, manipulation, and study of complex networks of nodes and edges that is widely used for various types of network analyses, including social network mapping [21]. For example, NetworkX library’s **graph()** function allows researchers to initialize and build network structures, which can then be analyzed and visualized. The **nx.draw()** function allows researchers to set visual parameters for the network map appearance (including node, edge, font definition, position, size, and color) (<https://networkx.org/documentation/stable/reference/generated/networkx.drawing.nx_pylab.draw.html>).

Another advantage of Python is the ability to use it on the cloud-based platform **Google Colab**, which makes Python more accessible by enabling users to write and execute code in a web browser without any setup, offering free access to computational resources like Graphics Processing Units (GPUs, specialized hardware designed to accelerate the rendering of images and parallel processing tasks).

The two network mapping protocols tools (Kumu and Python) were applied to a previous qualitative analysis (Bray et al., 2022) to test their real-world application and provide a side-by-side comparison of strengths and limitations associated with each approach.

# Methods

## Original (Primary) Data

Binge eating disorder is an autonomous eating disorder diagnosis recognized in the American Psychological Association’s Diagnostic Statistical Manual, 5th Edition, text revision (DSM-V-TR) [22]. Binge eating disorder is characterized by discrete rapid consumption of objectively large amounts of food without compensation, associated with loss of control and distress [22]. Environmental factors that contribute to binge eating disorder continue to evolve, as does our understanding of these factors in the field [1,23]. Therefore, in Bray et al., 2022, we conducted a cross-sectional, mixed-methods study of environmental factors that expert binge eating disorder researchers, clinicians, and healthcare administrators associate with binge eating disorder. Fourteen expert binge eating disorder researchers, clinicians, and healthcare administrators were identified internationally based on federal funding, PubMed-indexed publications, active practice in the field, leadership in relevant societies, and/or clinical and popular press distinction. Semi-structured interviews were recorded anonymously and analyzed by ≥2 investigators using reflexive thematic analysis and quantification. Identified themes included: (1) invalidation and invalidating environments (100% expert endorsement); (2) systemic issues and systems of oppression (100%); (3) marginalized and under-represented populations (100%); (4) economic precarity (93%); (5) stigmatization and its psychological impacts (93% endorsement); (6) trauma and adversity (79% endorsement); (7) food insecurity/scarcity (64%); (8) interpersonal factors (64% endorsement); (9) social messaging and social media (50% endorsement); (10) nutrition insecurity/scarcity (43%); (11) predatory food industry practices (29% endorsement); and (12) research/clinical gaps and directives (100% endorsement).

Expert recognition and literature findings suggest the environmental factors identified in Bray et al., 2022 often intersect and interact in a variety of complex ways that often disproportionately impact specific vulnerable populations. For example, findings suggest racial, ethnic, sexual, and trans/nonbinary gender minorities are more likely to experience discrimination [24-32] and stigmatization [30,33-37];, homelessness [38], unemployment [39], poverty [39], and food insecurity [40-42], direct targeting by tobacco-owned food and beverage marketing programs [43], and less likely to be included in eating disorder research [44], screened by healthcare providers for an eating disorder [45,46], recognize the need for binge eating disorder treatment when present [47], and less likely to receive treatment when needed [44,45,47-51]. Each of these factors have been independently linked to increasing risk for binge eating disorder [33,52-55] and it is likely that experiencing more than one factor exponentially increases the risk for developing binge eating disorder, specifically among racial, ethnic, and sexual minorities. Thus, in this example alone, we can identify that the primary theme of marginalized and under-represented populations (theme 3) has overt relationships with the following additional themes: (2) systemic issues and systems of oppression, (4) economic precarity, (5) food insecurity/scarcity, (6) nutrition insecurity/scarcity, (7) stigmatization and its psychological impacts, (11) predator food industry practices, and (12) research/clinical gaps and directives, as well as implied relationships with trauma and aversity, interpersonal factors, and social media.

Here, the themes and subthemes identified in Bray et al., 2022 – as well as the number and percent of participants who endorsed each theme and the way the themes were described in Bray et al., 2022 (by experts and in the literature) as relating (or not relating) to one another – were used as primary data entered into Kumu and Python as mapping entities/nodes for network mapping visualization (as described below).

Table . Environmental Factors Associated with Binge Eating Disorder by Experts in the Field, as Published in Bray et al., 2022 (Full Table in Supplemental Table S1)

| **Table 1. Environmental Factors Associated with Binge Eating Disorder by Experts in the Field, as Published in Bray et al., 2022 (Full Table in Supplemental Table S1)** |
| --- |
| **Theme** | **Expert Endorsement # (%)** |
| I. Invaliding Environments & Experiences\* | 14 (100%) |
|  i. Marginalized and under-represented populations |  14 (100%) |
|  ii. Systemic Discrimination |  12 (82%) |
|  iii. Media messaging and sociocultural ideals/mandates |  12 (82%) |
|  iv. Insurance and healthcare systems |  9 (64%) |
|  v. Predatory Food Industries/Environments |  4 (29%) |
|  vi. Abuse (sexual, emotional, or physical) |  4 (29%) |
|  vii. Geographic systems1 |  4 (29%) |
|  viii. Eating disorder research as a field2 |  3 (21%) |
|  ix. Federal funding for eating disorder research3 |  2 (14%) |
|  x. Economic exploitation4 |  1 (7%) |
|  xi School systems |  1 (7%) |
|  xii. Legal systems |  1 (7%) |
|  xiii. Justice systems (police harassment) |  1 (7%) |
| II. Systematic Issues & Systems of Oppression | 14 (100%) |
|  i. Systemic Discrimination |  12 (82%) |
|  ii. Media messaging and sociocultural ideals/mandates |  12 (82%) |
|  iii. Insurance and healthcare systems |  9 (64%) |
|  iv. Predatory Food Industries/Environments |  4 (29%) |
|  v. Abuse (sexual, emotional, or physical) |  4 (29%) |
|  vi. Geographic systems1 |  4 (29%) |
|  vii. Eating disorder research as a field2 |  3 (21%) |
|  vii. Federal funding for eating disorder research3 |  2 (14%) |
|  vii. Economic exploitation4 |  1 (7%) |
|  vii. School systems |  1 (7%) |
|  vii. Legal systems |  1 (7%) |
|  vii. Justice systems (police harassment) |  1 (7%) |
| III. Marginalized and under-represented populations | 14 (100%) |
|  i. Low socioeconomic status/economic insecurity |  13 (93%) |
|  ii. Food or nutrition scarcity |  10 (71%) |
|  iii. Male sex/gender |  8 (57%) |
|  iv. Racial and ethnic minorities (e.g., BIPOC) |  5 (36%) |
|  v. Lesbian, gay, bisexual, transgender, queer, two-souled, nonbinary, other (LGBTQ2+) |  3 (21%) |
|  vi. Age |  2 (14%) |
|  vii. Religion |  1 (7%) |
| IV. Economic Insecurity  | 13 (93%) |
|  i. Economic aspects of binge eating disorder |  13 (93%) |
|  ii. Potential mediators/moderators of relationship between economic status & BED pathology |  9 (64%) |
| V. Stigmatization and its Psychological Impacts | 13 (93%) |
|  i. Forms of stigmatization recognized as relevant to BED |  13 (93%) |
|  ii. Body weight/shape/size stigmatization described as: |  11 (79%) |
| VI. Trauma and Adversity | 11 (79%) |
|  i. Relevant forms of trauma/adversity |  7 (50%) |
|  ii. Relationship between trauma/adversity & BED |  11 (79%) |
|  iii. Critical considerations |  5 (36%) |
| VII. Food Insecurity | 9 (64%) |
|  i. Potentially disrupting one’s relationship with food or eating |  5 (36%) |
|  ii. Linked to economic insecurity |  5 (36%) |
|  iii. Increasing risk for other physical and psychological health problems |  4 (29%) |
|  iv. Linked to the COVID-19 pandemic |  2 (14%) |
|  v. Childhood adverse food experiences as important ACES12 |  1 (7%) |
| VIII. Interpersonal Factors | 9 (64%) |
|  i. Ways interpersonal deficits or negative interpersonal relationships can impact BED | 7 (50%) |
|  ii. Ways aspects of BED can contribute to interpersonal deficits | 5 (36%) |
|  iii. Impacts of interpersonal factors on BED pathology | 9 (64%)15 |
| IX. Social Messaging and Social Media | 7 (50%) |
|  i. Significantly relevant to binge eating disorder pathology | 7 (50%) |
|  ii. Relationship described as exclusively negative17 | 4 (28%) |
|  iii. Relationship described as primarily negative but with some positive aspects or potential | 3 (21%) |
|  iv. Relationship described as exclusively positive | 0 (0%) |
| X. Nutrition Scarcity | 6 (43%) |
|  i. Linked to socioeconomic status | 4 (29%) |
|  ii. Linked to food environment | 3 (21%) |
|  iii. Cited research findings linking nutrition scarcity to binge eating and obesity18 | 1 (7%) |
|  iv. Cited research relating urbanization factors to increased risk for BED19 | 1 (7%) |
| XI. Predatory Food Industry Practices | 4 (29%) |
|  i. “Predatory” food industry practices described20 | 4 (29%) |
|  ii. Food industry practices described as public policy issue | 2 (14%) |
|  iii. Call for public education21 | 2 (14%) |
|  iv. Express view that disordered eating behavior can be associated with specific foods, but can be extinguished | 2 (14%) |
|  v. Rewarding food properties acknowledged but not described as intentionally engineered | 1 (7%) |
| XII. Research and Clinical Gaps | 14 (100%) |
|  i. Need for change in the systems that abet BED | 10 (71%) |
|  ii. Understanding the role of environmental impact/risk factors on BED | 5 (36%) |
|  iii. Inclusion of minority and marginalized populations | 4 (29%) |
|  iv. Recognizing and understanding weight bias/stigma/discrimination | 4 (29%) |
|  v. Taking & understanding the narrative of individuals with BED | 3 (21%) |
|  vi. Understanding consequences of BED | 2 (14%) |
| **Table 1: Environmental Factors Associated with Binge Eating Disorder by Experts in the Field, as Published in Bray et al., 2022.** A recent cross-sectional mixed-methods study of binge eating disorder experts' opinions (Bray et al., 2022) identified twelve themes (originally collapsed into 9 but expanded into 12 here) and many subthemes that experts endorsed as environmental factors relevant to binge eating disorder. These included: (1) invalidating environments (100% expert endorsement); (2) systemic issues and systems of oppression (100% expert endorsement); (3) marginalized and under-represented populations (100% expert endorsement); (4) economic precarity (93% expert endorsement); (5) stigmatization and its psychological impacts (93% endorsement); (6) trauma and adversity (79% endorsement); (7) food insecurity (64% endorsement); (8) interpersonal factors (64% endorsement); (9) social messaging and social media (50% endorsement); (10) nutrition scarcity (43% endorsement); (11) predatory food industry practices (29% endorsement); and (12) research/clinical gaps (100% endorsement).**Table Legend:** Results expressed as n (%), in which percentages are n/14 times 100. **Table Footnotes:** \*Subthemes that endorsed the role of invalidating environments and experiences in BED pathology were largely identical to those endorsed for the role of systemic issues and systems of oppression (Theme II here) and marginalized, invalidated, and under-resourced communities (Theme III here). 1Defined as a relationship in economic wealth distribution wherein a worker does not receive proper compensation for his/her work (Arnold, 1995), e.g., from an employer or with a spouse. 2E.g., geographical inequities in provider and treatment access, and in the Supplemental Nutrition Assistance Program (SNAP) that can limit its effectiveness (Levine 2018; Hoynes *et al.,* 2022; Ziliak 2016) treatment access. 3E.g., operating from an anorexic-centric perspective/understanding. 4E.g., lack of funds for eating disorder research relative to disorders of similar prevalence lack of clarity regarding what agencies should fund eating disorder research. 5E.g., individuals in larger bodies experience economic discrimination. 6E.g., males, specific ethnicities. 7Especially when occurring during childhood or chronically 6,8Suggests different ethnicities may have different levels of acceptance around weight that impact distress frequency and treatment seeking. 9E.g., being forced to run in gym class and ridiculed by peers. 10“There’s that trauma of [the belief that] ‘taking care of myself [is] bad and selfish, and I shouldn’t do that.,’ and even if they can’t verbalize that [view], it’s there,” (P37). 11or resulting mood regulation disturbances. 12Adverse childhood experiences that are often overlooked and under-screened, but that potentially relate to adult eating disorder pathology. 13E.g., poor communication skills or social interaction abilities. 14E.g., systemic discrimination and stigmatization. 15Two participants made statements about negative relationships between interpersonal factors and BED pathology AND about positive relationships between social interaction and BED pathology. 16Outside of social media and social messaging. 17Primarily by reinforcing ideals around body weight/shape/ size, food, eating, and fitness that contribute to social ranking, social interactions, and self-esteem/valuation/negative affect. 18Three separate areas of research demonstrate that: a) malnutrition can occur in individuals with larger bodies, b) malnutrition can lead to food preoccupation [56]; and c) maternal malnutrition is linked to offspring obesity (e.g., Although the participant mis-referenced Aamodt, 2016 [57] – which cites Tripicchio *et al*., 2014 [58] – Parlee *et al.* [59] note the Dutch famine study found gestational maternal malnutrition increases odds of offspring adult obesity (Ravelli et al., 1976, 1998, 1999 in Parlee *et al.,* 2014) and animal studies find maternal nutrient-or protein deficiency causes adult offspring obesity (see citations 57–78 in Parlee *et al.*, 2014) [59]. 19E.g., food and nutrition insecurity and poverty [60]. 20E.g., hiring engineers to design foods that produce specific rewarding or emotional responses and promote consumption, potentially leading to over-consumption and binge eating. 21E.g., informing individuals with binge eating disorder of the nature of “hyper-engineered foods” and food industry practices to provide a full picture of “[the foods and industries] they’re dealing with,” (P16). 22Including need for more funding (equally proportionate to that available for research on other disorders of similar magnitude) and need for clarification on which funding agencies should fund eating disorder research. 23E.g., structural racism and sexism, economic exploitation (see statements from P16 in section A), and “broader sociocultural issues.” 24“What do we do then to reach these [marginalized] communities in a way that's meaningful?”**Table Abbreviations:** **ACEs**, adverse childhood experiences; **BED**, binge eating disorder; **COVID-19**, Coronavirus-19; **NIDDK**, National Institute of Diabetes and Digestive and Kidney Diseases; **NIH**, National Institute of Health; **NIMH**, National Institute of Mental Health. |

## Study 1: Social Network Mapping Using Online Platform Kumu

### Network Mapping

Kumu’s secure web-based visualization platform (<https://kumu.io/>, CA, USA) was used to organize data into relationship maps to enable better data visualization and analysis, following the methods used by Biddell et al., 2022.

### Data Security & Privacy

Kumu is a secure software platform with end-to-end encryption. Kamu’s privacy and security policies are available online:<https://kumu.io/privacy>; [https://kumu.io/security](%20https%3A//kumu.io/security). For this study, only de-identified published data was uploaded onto Kumu. No individually identifiable information (e.g., personal health information) was transferred or stored onto Kumu.

### Data Structuring and Import into the Network Mapping Site

The themes and subthemes identified in Bray et al., 2022 – and the number and percent of participants who endorsed each theme – were entered into Kamu as mapping entities.

### Elements Sheet

An elements sheet was used to assign labels (themes) identified in the original data [1] and provide brief descriptions of each element (theme) based on the secondary data analysis. Each theme was represented in the 'Labels' column, with descriptions provided in a second ‘Description’ column.

### Relational Data Sheet

A relational data sheet was used to document the relationships between themes, as determined through secondary reflexive engagement with the primary data [1]. Separate columns were used to represent primary themes and corresponding subthemes (represented in two separate columns labeled ‘From’ (primary themes) and ‘To’ (corresponding subthemes). A third ‘Direction’ column was used to indicate the nature of the connection between themes and a fourth ‘Description’ column was sued to provide additional details as needed.

### Thematic Transformation, Visualization, & Strength

Kumu was used to transform the matrix-like data from the elements and relational data sheets into a network map, integrating principles of social network mapping and concept mapping.

Each entity (e.g., each primary theme identified in Bray et al., 2022) was represented by a different colored icon in the map to enable effective element visualization **(Figure 1).** The strength of each theme was determined using the number and percent of participants who endorsed the theme, as reported in Bray et al., 2022. This was represented by the thematic circle thickness (diameter) on the map. Thicker circles with larger diameters represent higher percentage of participant endorsement of a specific theme or subtheme.

Themes/elements with higher endorsement percentages were positioned at the center of the network map, while those with lower percentages were positioned in the periphery.

## Study: 2 Social Network Mapping using Python Programming

### Network Mapping

The themes and subthemes identified in Bray et al., 2022 were structured into a relational matrix and the Python mapping library **dyconnmap** (<https://github.com/makism/dyconnmap>) was used for network map visualization, as described below.

### Data Security & Privacy

Python itself is a programming language and does not inherently provide end-to-end encryption or security features. However, the Python Software Foundation (PSF) does have a Privacy Notice and Security Policy, as well as a security response team (the Python Security Response Team, PSRT) that handles security issues and vulnerabilities. The PSF Privacy Notice and the PSF Security Policy documents are available online: <https://policies.python.org/PSF-Privacy-Notice/>, <https://www.python.org/dev/security/> [61,62]. Additionally, none of the libraries used in this work have known security vulnerabilities. For this study, only de-identified published data was uploaded onto Python. No individually identifiable information (e.g., PHI) was transferred to or stored inside a Python environment.

### Coding

ChatGPT.com [63] was used to generate code for the network mapping, including data preparation, network initialization, edge creation, visualization parameters, graph layout, and display, as described in the **Supplemental Material S2.** Please note that no data was uploaded to ChatGPT.com.

### Data Structuring and Import into the Network Mapping Site

#### Data Preparation

Microsoft Excel (Microsoft Corporation, <https://www.microsoft.com/en-us/microsoft-365/excel>) [64] and Google Sheets (Google LLC, <https://www.google.com/sheets/about/>) [65] were both (separately) used to create a heat-map-style relational matrix, with primary themes identified in the original data (Bray et al., 2022) populated horizontally into row 1 and vertically into column 1. Binary coding was used to code for the presence (1) or absence (0) of relationships between horizontal/row and vertical/column elements (themes). The documents were saved in CSV format for ease of use in Python.

#### Importing Python Packages

Four Python libraries were imported and used for data processing, mapping and visualization. These include **Pandas, NumPy**, **Matplotlib and NetworkX**. Some of the relevant functionalities imported include the **pyplot** plotting interface, the **colors** module, and the **HSV**function from **Matplotlib;** and **graph()** and **nx.draw()** functions from **NetworkX**. Descriptions of these libraries and functions can be found in the introduction and in the **Supplemental Material S3.**

#### Data Loading

The CSV data file(s) were added to Google Collaboratory (AKA “Google Collab;” <https://colab.google>, <https://colab.research.google.com>) [66]. The **Pandas** library was used to load and read the CSV file.

#### Data Transformation & Mapping

Data from the CSV file was transformed into a network map using the NetworkX library, integrating principles of social network mapping and concept mapping. The **graph()** function was used to initialize the network structure, with data frame rows and columns defined as primary themes identified in the original data in Bray et al., 2022. These were used to define the main elements/actors in the network map, with each actor representing an individual node in the network list, thus depicting how each node (primary theme identified in Bray et al., 2022) connects and interacts with other nodes. The NetworkX library’s **nx.draw()** function was used to set visual parameters for the network map appearance (including node, edge, font definition, position, size, and color). These are described in further detail in the **Supplemental Material S4.**

#### Map Optimization & Visualization

To ensure optimal visual layout, a **spring\_layout algorithm** was used with a seed value of 42 [21]. Matplotlib library’s HSV function was used to assign a unique color to each node to optimize visualization. TheMatplotlib library’s **plt.show()** function was used to display the network map as an open figure **(Figure 2)**. Additional detail on the thematic transformation, visualization, and optimization can be found in the **Supplemental Material S4.**

# Results

## Original (Primary) Data

All fourteen experts (14/14, 100%) responded to the domain question asking participants to describe their perspectives or knowledge on literature and research, current clinical guidelines, and their own personal (professional) experiences relating to current CIH treatment interventions utilized and/or considered for clinical care and treatment of adult binge eating disorder.

## Study 1: Social Network Mapping Using Online Platform Kumu

The Kumu network map (Figure 1) visually represented the relationships between themes identified in Bray et al., 2022. The map highlighted the centrality of themes such as invalidation and invalidating environments, systemic issues and systems of oppression, and marginalized and under-represented populations. These themes were positioned at the center of the map, indicating their high endorsement percentages and central role in the network of environmental factors contributing to binge eating disorder. Peripheral themes included predatory food industry practices and nutrition insecurity/scarcity, which had lower endorsement percentages and were positioned more towards the edges of the map.

## Study 2: Social Network Mapping using Python Programming

The Python-generated network map (Figure 2) provided a similar visual representation of the relationships between themes identified in Bray et al., 2022. The map also highlighted the centrality of themes such as invalidation and invalidating environments, systemic issues and systems of oppression, and marginalized and under-represented populations. Peripheral themes included predatory food industry practices and nutrition insecurity/scarcity. The Python-generated map allowed for more detailed customization of visual parameters, providing a more tailored and precise representation of the network.

## Comparison of Kumu and Python Network Mapping Approaches

Both Kumu and Python network mapping approaches effectively visualized the relationships between themes identified in Bray et al., 2022. However, there were notable differences in the customization and flexibility of the two approaches. Kumu’s user-friendly interface and interactive features makes it accessible for users with limited technical skills, while Python’s extensive library ecosystem allowed for more detailed and precise customization of the network map. The choice between the two approaches will depend on the specific needs and technical expertise of the user.

## Figure 1: Social Network Mapping Using Kumu’s Online Platform

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Figure 1: Kumu Network Map of Environmental Factors that Experts in the Field Associated with Binge Eating Disorder in Bray et al., 2022. Kumu’s secure web-based visualization platform (<https://kumu.io/>, CA, USA) was used to organize primary data from Bray et al., 2022 into relationship maps to visualize and analyze the data. The themes identified in Bray et al., 2022 – and the number and percent of participants who endorsed each theme – were entered into Kamu as mapping entities, with each theme (entity) representing an individual circle on the primary map. The strength of each theme was determined using the number and percent of participants who endorsed the theme, as reported in Bray et al., 2022. This was represented by the thematic circle thickness (diameter) on the map. Thicker circles with larger diameters represent higher percentage of participant endorsement of a specific theme or subtheme. The network map visually represents the relationships between themes identified in Bray et al., 2022. The map highlights the centrality of themes such as invalidation and invalidating environments, systemic issues and systems of oppression, and marginalized and under-represented populations. These themes are positioned at the center of the map, indicating their high endorsement percentages and central role in the network of environmental factors contributing to binge eating disorder. Peripheral themes include predatory food industry practices and nutrition insecurity/scarcity, which have lower endorsement percentages and are positioned more towards the edges of the map.

## Figure: 2 Social Network Mapping using Python Programming



Figure 2: Python Network Map of Environmental Factors Experts in the Field Associated with Binge Eating Disorder in Bray et al., 2022.

Python mapping (<https://github.com/makism/dyconnmap>) was used to organize themes and subthemes identified in Bray et al., 2022 into a relational matrix used for network map visualization and analysis. The NetworkX library [21] was imported to create and visualize the network map. The graph() function was used to initialize the network structure, and the nx.draw() function was used to set visual parameters for the network map appearance (including node, edge,font definition, position, size, and color). The data from the CSV file was transformed into a network map using the NetworkX library, integrating principles of social network mapping and concept mapping. Each entity (e.g., each primary theme identified in Bray et al., 2022) was represented by a different colored icon in the map to enable effective element visualization. The strength of each theme was determined using the number and percent of participants who endorsed the theme, as reported in Bray et al., 2022. This was represented by the thematic circle thickness (diameter) on the map. Thicker circles with larger diameters represent higher percentage of participant endorsement of a specific theme or subtheme. Themes/elements with higher endorsement percentages were positioned at the center of the network map, while those with lower percentages were positioned more peripherally. The network map visually represents the relationships between themes identified in Bray et al., 2022. The map highlights the centrality of themes such as invalidation and invalidating environments, systemic issues and systems of oppression, and marginalized and under-represented populations. These themes are positioned at the center of the map, indicating their high endorsement percentages and central role in the network of environmental factors contributing to binge eating disorder. Peripheral themes include predatory food industry practices and nutrition insecurity/scarcity, which have lower endorsement percentages and are positioned more towards the edges of the map. This map allows for more detailed customization of visual parameters, providing a more tailored and precise representation of the network.

# Discussion

This study explored the use of two different network mapping software and techniques – Kumu and Python – to develop network mapping protocols that provide visual representations of qualitative data analysis findings. The application of these protocols to a previous qualitative analysis (Bray et al., 2022) demonstrated their real-world utility and provided a side-by-side comparison of their strengths and limitations.

## Novelty and Innovation

The novelty of this study lies in its application of network mapping tools, traditionally used in fields like neuroscience and public health, to qualitative data analysis in social sciences like psychology. This innovative approach enhances the visualization and understanding of complex relationships between themes, offering a new method for qualitative researchers to present their findings.

The potential for this innovation should not be minimized, particularly in fields that rely on qualitative data. The application of network mapping to qualitative data has potential to add a layer of objective statistical modeling that can (a) enable visual data representation, (b) support greater scientific rigor, and (c) enable exploration of the often-complex ways a variety of real-life variables interact with one another, which cannot otherwise be done (well) verbally.

## Relevance of Findings to the Literature

While network mapping tools have been widely used in other fields, their application to qualitative data analysis in social sciences like psychology is relatively novel. This study builds on existing literature by demonstrating the utility of these tools in visualizing complex qualitative data, providing a new perspective on how qualitative findings can be represented and analyzed.

## Implications

The findings of this study have important implications for clinical practice and research. The use of network mapping approaches can enhance the visualization and analysis of qualitative data, providing a more comprehensive understanding of complex relationships between themes *and* a means for communicating a large amount of complex data through one or two succinct infographics. This approach can enable better translation and use of qualitative data findings in the more quantitative areas, including clinical and public health and policy fields. In our case, applying network mapping to the original data in Bray et al., 2022 provides insights that can be used to inform the development of more holistic targeted interventions and policies to address the environmental factors contributing to binge eating disorder.

## Software/Protocol Limitations, Strengths, & Comparisons

Both Kumu and Python network mapping approaches have their strengths and limitations. Kumu’s user-friendly interface and interactive features make it accessible for users with limited technical skills, while Python’s extensive library ecosystem allows for more detailed and precise customization of the network map. However, Kumu’s interface may limit the level of customization available, while Python’s extensive customization options may require more technical expertise. The choice between the two approaches may depend on the specific needs and technical expertise of the user. Specific comparisons are shown in **Table 2** below.

Table . Comparison of Kumu vs. Python Network Mapping Protocols for Qualitative Analysis

| **Table 2. Comparison of Kumu vs. Python Network Mapping Protocols for Qualitative Analysis** |
| --- |
| **Feature** | **Kumu** | **Python** |
| **User Interface** | User-friendly, web-based platform with interactive features | Requires coding knowledge, more technical interface |
| **Customization** | Limited customization options | Extensive customization options through various libraries |
| **Accessibility** | Accessible to users with limited technical skills | Requires technical expertise in programming |
| **Data Security & Privacy** | Secure platform with end-to-end encryption | Secure platform with end-to-end encryption |
| **Visualization** | Interactive network maps with basic visual parameters | Highly customizable visualizations with detailed parameters |
| **Library Ecosystem** | Limited to Kumu’s built-in features | Extensive ecosystem of libraries (e.g., NetworkX, Matplotlib) |
| **Ease of Use & Accessibility** | Easy to use for non-technical users | Requires technical expertise in programming and familiarity with Python and its libraries |
| **Application** | Suitable for social science and psychology researchers | Suitable for a wide range of scientific fields, including computational biology and advanced statistical modeling |
| **Strength Representation** | Thematic circle thickness based on participant endorsement | Thematic circle thickness based on participant endorsement |
| **Positioning of Themes** | Central themes positioned at the center, peripheral themes at the edges | Central themes positioned at the center, peripheral themes at the edges |
| **Cost** | Subscription-based service | Free and open-source |
| **Customization** | Limited customization options | Extensive customization options through various libraries |
| **Data Security & Privacy** | Secure platform with end-to-end encryption | Secure platform with end-to-end encryption |
| **Visualization** | Interactive network maps with basic visual parameters | Highly customizable visualizations with detailed parameters |
| **Table 2. Comparison of Kumu vs. Python Network Mapping Protocols for Qualitative Analysis.** |

## Study Limitations and Strengths

This study has several limitations and strengths that should be considered when interpreting the findings. One limitation is the reliance on previously published qualitative data (e.g., Bray et al., 2022), which may not have captured all relevant themes or relationships. Additionally, the use of binary coding for relationships between themes in the Python application may oversimplify the complexity of these relationships. Another limitation is the potential for bias in the secondary analysis and interpretation of the data.

However, this study also has several strengths. The use of two different network mapping approaches (Kumu and Python) allows for a comprehensive comparison of their utility and effectiveness in visualizing qualitative data. The application of these tools to a real-world dataset demonstrated their practical relevance and potential for enhancing qualitative data analysis. Furthermore, the study highlights the importance of visualizing complex relationships between themes, which can inform future research and practice.

Additionally, a major strength of this study (as addressed above) is its potential for innovation to the field of qualitative analysis. The application of network mapping to qualitative data has potential to add a layer of objective statistical modeling that can (a) enable visual data representation, (b) support greater scientific rigor, and (c) enable exploration of the often-complex ways a variety of real-life variables interact with one another, which cannot otherwise be done (well) verbally.

Lastly, the strengths and limitations addressed in the primary study (Bray et al., 2022) apply to the primary data used in this study as well.

## Conclusions

In conclusion, the use of network mapping approaches in this study provided valuable visual representations of the relationships between themes identified in Bray et al., 2022. The Kumu and Python network maps highlighted the centrality of key themes and the interconnectedness of environmental factors contributing to binge eating disorder. The choice between Kumu and Python may depend on the specific needs and technical expertise of the user. Future research should continue to explore the use of network mapping tools and techniques

# Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

# Author Contributions

Conceptualization, R.L. and B.B.; methodology, R.L., B.B., R.T.; visual network mapping, R.L.; secondary data analysis used to determine relationship between themes and subthemes: BB, RL, investigation, R.L., B.B., and R.T.; resources, B.B.; data curation, R.L., B.B.; writing – original draft preparation, B.B., R.T., R.L.; writing – review and editing, B.B., R.T., R.L., C.B., H.Z., and R.B.; supervision, B.B.; project administration, B.B. All authors agree to be accountable for the content of the work.

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