**Supplementary Material**

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

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Table S. Environmental Factors Associated with Binge Eating Disorder by Experts in the Field, as Published in Bray et al., 2022

| **Table S1. Environmental Factors Associated with Binge Eating Disorder by Experts in the Field, as Published in Bray et al., 2022** |
| --- |
| **Theme** | **Expert Endorsement # (%)** |
| I. Invaliding Environments & Experiences\* | 14 (100%) |
|  i. Marginalized and under-represented populations |  14 (100%) |
| a. Low socioeconomic status/economic insecurity | 13 (93%) |
| b. Food or nutrition scarcity | 10 (71%) |
| c. Male sex/gender | 8 (57%) |
| d. Racial and ethnic minorities (e.g., BIPOC) | 5 (36%) |
| e. LGBTQ2+ | 3 (21%) |
| f. Age | 2 (14%) |
| g. Religion | 1 (7%) |
|  ii. Systemic Discrimination |  12 (82%) |
| a. Body weight/shape/size discrimination | 12 (82%) |
| b. Structural racism | 2 (14%) |
| c. Structural sexism | 1 (7%) |
|  iii. Media messaging and sociocultural ideals/mandates |  12 (82%) |
| a. Perpetuating stigmatization | 12 (82%) |
| b. Body weight/shape/size ideals & discrimination | 12 (82%) |
| c. “Diet culture” | 3 (21%) |
| d. Movement & fitness ideals | 2 (14%) |
|  iv. Insurance and healthcare systems |  9 (64%) |
| a. Insurance costs and coverage | 6 (43%) |
| b. Systemic stigmatization from healthcare providers | 6 (43%) |
| c. Geographical access to treatment resources | 4 (29%) |
| d. Mandated movement for individuals in larger bodies | 2 (14%) |
| e. Provider scarcity | 1 (7%) |
|  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%) |
| a. Body weight/shape/size discrimination | 12 (82%) |
| b. Structural racism | 2 (14%) |
| c. Structural sexism | 1 (7%) |
|  ii. Media messaging and sociocultural ideals/mandates |  12 (82%) |
| a. Perpetuating stigmatization | 12 (82%) |
| b. Body weight/shape/size ideals & discrimination | 12 (82%) |
| c. “Diet culture” | 3 (21%) |
| d. Movement & fitness ideals | 2 (14%) |
|  iii. Insurance and healthcare systems |  9 (64%) |
| a. Insurance costs and coverage | 6 (43%) |
| b. Treatment costs | 6 (43%) |
| c. Systemic stigmatization from healthcare providers | 6 (43%) |
| d. Geographical access to treatment resources | 4 (29%) |
| e. Mandated movement for individuals in larger bodies | 2 (14%) |
| f. Provider scarcity | 1 (7%) |
|  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%) |
| a. Direct connections between BED pathology & economic status | 5 (36%) |
|  ii. Potential mediators/moderators of relationship between economic status & BED pathology |  9 (64%) |
| a. Food insecurity | 5 (36%) |
| b. Nutrition access/scarcity | 5 (36%) |
| c. Food environment | 3 (21%) |
| d. Mental health risks | 2 (14%) |
| e. COVID-10 pandemic | 2 (14%) |
| f. Access to treatment resources | 2 (14%) |
| g. Weight biases and descrimination5 | 1 (7%) |
| V. Stigmatization and its Psychological Impacts | 13 (93%) |
|  i. Forms of stigmatization recognized as relevant to BED |  13 (93%) |
| a. Body weight/shape/size stigmatization and discrimination | 12 (82%) |
| b. Eating disorder diagnosis stigmatization | 5 (36%) |
| c. Mental health diagnosis stigmatization  | 5 (36%) |
| d. Any medical diagnosis stigmatization  | 1 (7%) |
| e. Stigmatization around perfectionistic food/eating ideals | 1 (7%) |
| *These stigmatizations suggested as having higher prevalence in specific populations6* | 2 (14%) |
|  ii. Body weight/shape/size stigmatization described as: |  11 (79%) |
| a. Potentially exacerbating BED symptoms and severity | 11 (79%) |
| b. Prevalent among healthcare providers and in the medical system | 6 (43%) |
| c. Core to BED pathology | 4 (29%) |
| d. Area requiring better understanding of its trajectory and impact | 4 (29%) |
| e. Traumatic7 | 3 (21%) |
| f. Possibly varying by ethnicity8 | 1 (7%) |
| VI. Trauma and Adversity | 11 (79%) |
|  i. Relevant forms of trauma/adversity |  7 (50%) |
| a. Abuse (sexual, emotional, or physical; esp. early childhood abuse) | 4 (29%) |
| b. Body weight/shape/size stigmatization | 3 (21%) |
| c. COVID-19 pandemic | 3 (21%) |
| d. Invalidating/oppressive experiences/environments | 2 (14%) |
| e. Interpersonal trauma | 2 (14%) |
| f. Mandated movement or physical activity9 | 2 (14%) |
| g. Childhood of food scarcity/insecurity as ACES | 1 (7%) |
| h. Chronic dieting | 1 (7%) |
| i. Untreated diagnoses (e.g., ADHD) | 1 (7%) |
| j. Impacts of IBS | 1 (7%) |
| k. Trauma related to self-neglect and negative views on self-care10 | 1 (7%) |
|  ii. Relationship between trauma/adversity & BED |  11 (79%) |
| a. Trauma/adversity as relevant to BED psychopathology | 11 (79%) |
| Trauma/adversity highly relevant for a minority with that comorbidity |  1 (7%) |
| b. Trauma/adversity as increasing risk for BED | 5 (36) |
| Cited research findings |  2 (14%) |
| ACES can result in PTSD and BED |  2 (14%) |
| Trauma/adversity increase risk for m[any] psychiatric problems |  2 (14%) |
| Trauma/adversity often precede BED (not vice versa) |  1 (7%) |
| *Childhood* (but not adult) trauma/adversity as risk factor |  1 (7%) |
| PTSD highly comorbid with BED and food addiction |  1 (7%) |
| c. Neurobiological impacts of trauma/adversity may prime BED  |  2 (14%) |
| Negative impact on self-regulation  |  1 (7%) |
| d. Binge eating to cope with trauma/adversity11 | 2 (14%) |
| e. Trauma/adversity as exacerbate BED symptoms | 2 (14%) |
| f. Additional possible mechanistic pathways | 2 (14%) |
| Gut microbiota as possible underlying mechanism |  1 (7%) |
| IBS as mediator, moderator, and possible underlying mechanism |  1 (7%) |
| Stress as possible underlying mechanism |  1 (7%) |
| Trauma/adversity may burden BED treatment distress tolerance |  1 (7%) |
| g. Trauma/adversity as comorbid/coexisting |  1 (7%) |
|  iii. Critical considerations |  5 (36%) |
| a. Importance of addressing trauma and adversity in treatment | 4 (29%) |
| Importance of establishing *how* to address trauma/adversity history in treatment |  1 (7%) |
| b. Importance of screening for trauma and adversity | 2 (14%) |
| c. Need for greater understanding of the relationship between trauma/adversity and BED | 1 (7%) |
| d. Literature findings on poor self-report of trauma | 1 (7%) |
| 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%) |
| a. Social sensitivity related to social anxiety/fear/threat perception | 5 (29%) |
| b. Interpersonal deficits affecting relationships and social support13 | 3 (21%) |
| c. Socializing around food/eating as a problematic social activity | 3 (21%) |
| d. Social anxiety as a relevant comorbidity in BED | 3 (21%) |
| Referenced research on the role of social threat |  1 (7%) |
| Suggested social anxiety disorder is “the most common additional mental health problem for people with an eating disorder” |  1 (7%) |
| e. Spousal relationships, intimacy, and sexuality | 2 (14%) |
| f. Negative social experiences or deficiency communication directly catalyzing or contributing to binge eating behavior | 2 (14%) |
|  ii. Ways aspects of BED can contribute to interpersonal deficits | 5 (36%) |
| a. Body weight/shape/size stigmatization | 2 (14%) |
| b. Body weight/shape/size overvaluation | 1 (7%) |
| c. Social ranking | 1 (7%) |
| d. Broader social phenomenon14 | 1 (7%) |
| e. COVID-19 quarantine/isolation | 1 (7%) |
|  iii. Impacts of interpersonal factors on BED pathology | 9 (64%)15 |
| a. Negative relationship between interpersonal factors and BED pathology | 7 (36%) |
| b. Positive relationships between social interaction and BED pathology16 | 3 (21%)4 |
| Positive impacts of community |  2 (14%) |
| Benefits of family |  1 (7%) |
| IX. Social Messaging and Social Media | 7 (50%) |
|  i. Significantly relevant to binge eating disorder pathology | 7 (50%) |
| a. Social media as relevant |  5 (36%) |
| b. Social messages as relevant |  3 (21%) |
|  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%) |
| a. Describe foods intentionally designed to produce specific reward responses that promote excessive consumption |  2 (14%) |
| b. Comparisons made between “big tobacco” and “big food” industries |  2 (14%) |
|  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%) |
| a. Eating Disorder Field | 5 (36%) |
| Eating disorder research funding22 | 2 (14%) |
| Mandated movement perpetuated by healthcare system | 2 (14%) |
| Recognizing implicit weight bias/stigma/discriminating in the field | 1 (7%) |
| b. Food systems & availability | 4 (29%) |
| Food industry practices |  2 (14%) |
| Food stamp allotment |  1 (7%) |
| c. Other systems of oppression23 | 2 (14%) |
| d. Economic aspects that prevent treatment access | 1 (7%) |
|  ii. Understanding the role of environmental impact/risk factors on BED | 5 (36%) |
| a. Traumatic impacts of mandated movement | 2 (14%) |
| b. Impacts of trauma | 1 (7%) |
| c. Impacts of “broader sociocultural issues” | 1 (7%) |
| d. Impacts of community | 1 (7%) |
| e. Impacts of interpersonal threat/threat sensitivity | 1 (7%) |
| f. Impact of environmental pollution | 1 (7%) |
|  iii. Inclusion of minority and marginalized populations | 4 (29%) |
| a. Including and reaching men | 1 (7%) |
| b. Including individuals in normal-sized bodies | 1 (7%) |
| c. Identifying struggles unique to marginalized populations | 1 (7%) |
| d. Information dissemination24 | 1 (7%) |
|  iv. Recognizing and understanding weight bias/stigma/discrimination | 4 (29%) |
| a. Research investigation of forms, prevalence, and impacts | 4 (29%) |
| b. Recognizing implicit weight bias/stigma/discrimination in the field | 1 (7%) |
|  |  |
|  v. Taking & understanding the narrative of individuals with BED | 3 (21%) |
| a. Identifying how to “*listen for what people are telling us about their experience?*”  | 1 (7%) |
| b. Listening to- and understanding the unique experiences of individuals with BED | 1 (7%) |
|  vi. Understanding consequences of BED | 2 (14%) |
| a. Impacts on interpersonal relationships | 2 (14%) |
| b. Impacts on threat sensitivity | 1 (7%) |
| c. Impacts on expression of sexuality | 1 (7%) |
| **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 [1]; and c) maternal malnutrition is linked to offspring obesity (e.g., Although the participant mis-referenced Aamodt, 2016 [2] – which cites Tripicchio *et al*., 2014 [3] – Parlee *et al.* [4] 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) [4]. 19E.g., food and nutrition insecurity and poverty [5]. 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. |

# Supplementary Material S2: Generating Code for Network Mapping in Python

Chat GPT.com [6] was used to generate code for the network mapping. The following steps outline how Chat GPT was utilized to apply a network mapping protocol to qualitative data using Python:

1. **Data Preparation**: Chat GPT was used to generate Python code for loading and preparing the qualitative data. This included importing necessary libraries (e.g., Pandas, NumPy) and reading the CSV file containing the correlation matrix into a Pandas DataFrame.
2. **Network Initialization**: Chat GPT generated code to initialize the network structure using the NetworkX library. This involved creating a graph object and adding nodes representing the primary themes identified in the qualitative data.
3. **Edge Creation**: Chat GPT provided code to create edges (connections) between nodes based on the binary coding system applied to the qualitative data. This included iterating through the correlation matrix and adding edges for all 1-values, indicating a relationship between themes.
4. **Visualization Parameters**: Chat GPT generated code to set visual parameters for the network map using the NetworkX and Matplotlib libraries. This included defining node and edge attributes such as color, size, and position, as well as customizing the overall appearance of the network map.
5. **Graph Layout**: Chat GPT provided code to apply a spring layout algorithm to the network graph, ensuring optimal visual layout and spacing between nodes. A seed value was used to ensure consistent graphical layout across different runs.
6. **Display**: Finally, Chat GPT generated code to display the network map using Matplotlib’s plt.show() function, allowing for interactive visualization of the network structure.

# Supplementary Material S3: Importing Python Packages

The following Python packages were imported and used for data mapping and visualization: from **Python’s data science stack,** the **Python NumPy** **Library** (a computational science library that supports large multi-dimensional arrays with a large collection of operational mathematical functions) and the **Python Matplotlib** **Library** (a plotting library for creating static, animated, and interactive visualizations) were imported, including **matplotlib.pyplot**, **matplotlib.colors**, the **HSV function** , and the **plt.show() function** within the Matplotlib Library. **Matplotlib.pyplot** is a state-based interface to the Matplotlib library that enables static, animated, interactive, and simple cases of programmatic plot generations (visualizations) within Python (similar to MATLAB), through a collection of pyplot functions. Each pyplot function makes some change to a figure, such as creating a figure, creating a plotting area, plotting lines, and decorating the plot with labels [7,8]. For example, the **plot() function** in pyplot is used to create line plots. **Matplotlib.colors** is a module within Matplotlib that provides a set of functions and classes for handling colors. It includes utilities for converting colors between different color spaces (e.g., RGB to HSV), defining colormaps, working with named colors, and customizing the appearance of plots to ensure that visualizations are both informative and aesthetically pleasing [9,10]. Specifically, the Matplotlib Library/Matplotlib.colors’ **HSV function** converts color values into HSV format (Hue, Saturation, Value) to assign unique colors to each node, making graphs easier to understand. The **plt.show() function** is used to display all open figures. The function starts an event loop that identifies all currently active figure objects and opens one or more interactive windows that display object figures [7,11].

Outside of Python’s data science stack, the **Python NetworkX** library was also imported and used for data mapping and visualization, including the “**graph()**” and **“nx.draw()”** functions in particular. **Python’s NetworkX library** facilitates the creation, manipulation, and study of complex networks of nodes and edges that are widely used for various types of network analyses, including social network mapping [12]. 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, and font definition, position, size, color) [13,14].

# Supplementary Material S4: Transforming, Visualizing, & Optimizing Data in Python

Within the Python NetworkX library, the “**graph()**" function was used to create a network of nodes (primary themes identified in the original data (Bray et al., 2022)). The rows and columns of the data table (the data frame) were set to represent the primary themes identified in the original data (Bray et al., 2022). These were used to define the main elements (“actors”) in the network map. Each element (“actor”) was represented as a n individual node in the network list, thus depicting how each node (primary theme identified in Bray et al., 2022) are connected and interact with each other.

Using the binary coding system applied to the primary data to code for the presence (1) or absence (0) of correlations between themes (described in the “Data Preparation” section above), edges (connections or links between nodes in the network/graph) were made for all 1-values in the correlation matrix (e.g., all values in the correlation matrix with a correlation coefficient of 1, indicating a correlation between two variables). The edges were created in the correlation table using a nested loop (a repeated process to go through the data frame/table).

To ensure optimal visual layout, a **spring\_layout algorithm** was used with a seed value of 42. A spring layout algorithm is an automated method used to evenly position and arrange notes (items/primary themes) into a network graph with sufficient space between nodes and connections to prevent overlapping, comparable to placing a spring or buffer between objects to ensure separation. A seed value of 42 connotes a starting point given to an algorithm to ensure a consistent graphical layout with each loop/run. Matplotlib library’s HSV function was used to assign a unique color to each node to optimize visualization.

The NetworkX library’s **“nx.draw()”** function was used to set visual parameters for the network map appearance. Nodes were defined as primary themes identified in the original data (Bray et al., 2022). Edges were defined as correlations between nodes (as described above). Edge, node, and font positions, sizes, colors, and widths were also determined and set using the “nx.draw()” function.

TheMatplotlib Library’s **plt.show() function** was then used to display the network map as an open figure **(Figure 2)**.

# 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, C.B., H.Z., 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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