Obesity

Can the Participant Speak Beyond Likert? Free-Text Responses in COVID-19 Obesity Surveys

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Introduction

Research on lifestyle changes during the coronavirus disease (COVID-19) pandemic often relies on Likert-type scale question surveys (1-3). Survey participants respond to questions by selecting one of the numerically ordered choices "Strongly Disagree" = 1, "Disagree" = 2, "Neutral" = 3, "Agree" = 4, and "Strongly Agree" = 5. Analyzing Likert-type data requires statistical methods beyond approaches like linear regression (4). First, it is unclear whether the distance between choices is truly equal. For example, are Agree and Strongly Agree more close than Neutral and Agree? Second, summarizing results using traditional means makes little sense. For example, would a mean of 4.5 imply "Agree and a half" (5)? Finally, participants tend to select more central choices and less extremes (6).

Using natural language processing (NLP) (7,8), survey research can capture information from free-text response questions. Investigators are released from prescribing questions a priori and they gain more participant driven information. For example, "I have changed eating habits during quarantine" followed by Likert scale choices can be formulated as "Describe any changes in eating during quarantine." Here, we demonstrate the power of NLP to derive meaningful insights that enhance and improve traditional Likert surveys.

Methods

Obesity Action Coalition survey description

In May 2020, the Obesity Action Coalition fielded a survey of 1,114 US adults with 26 questions, including two free-text response questions. The survey utilized the SurveyMonkey public opinion research panel to obtain responses. The objective of this survey was to identify public perceptions about obesity, people with obesity, and weight bias. We analyzed 1,070 free-text responses to "In your opinion, what does the American public think of people with obesity?"

Sentiment analysis

Sentiment analysis segments text into individual words and then assigns a sentiment score to each word from a dictionary or lexicon (9). In the programming language R (9), the "nrc" lexicon maps each word to eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and as a positive or negative sentiment. By summing the sentiment scores of each word in a free-text response, an aggregate sentiment for the response and the number of words used in each of the eight emotion categories can be retained.

Using the "nrc" lexicon, sentiment was calculated for each response. Sentiment distribution by perceived weight status was generated. The word count in the eight basic emotions was retained.

Word frequency

Free-text response patterns can be tabulated by the frequency of words or phrases (n-grams) within a set of free-text responses. The top most frequent unigrams (individual words), bigrams (pairs of consecutive words), and trigrams (sets of three consecutive words) were tabulated and plotted as a bar chart. Stop words like "the," "of," and "to" were removed from the text (9). In addition, bigrams or trigrams with similar meanings were combined. For example, counts of "overweight people" were included in the "obese people" bigram.

Results

Sentiment analysis

In Figure 1A, the distribution of sentiments appears almost normal, with the average response slightly negative. Figure 1B demonstrates that emotions of disgust and fear were more common than emotions of trust and joy.

Figure 2A is a notched box plot of the sentiment against the Likert-type weight perception responses of "Very Underweight," "Somewhat Underweight," "About Right," "Somewhat Overweight," and "Very Overweight." The notches represent the 95% CIs of the median value. Figure 2B displays the sample size by box plot. The medians and CIs were lower (more negative sentiment) in the Somewhat Overweight and Very Overweight categories.

Word frequency

Figure 3 shows the most common unigrams, bigrams, and trigrams. The plot of unigrams shows some common expected words for the question, such as "people" and "obesity." The bigram and trigram plots reveal narratives such as "people are lazy" as a top perception of what the American public thinks of people with obesity.

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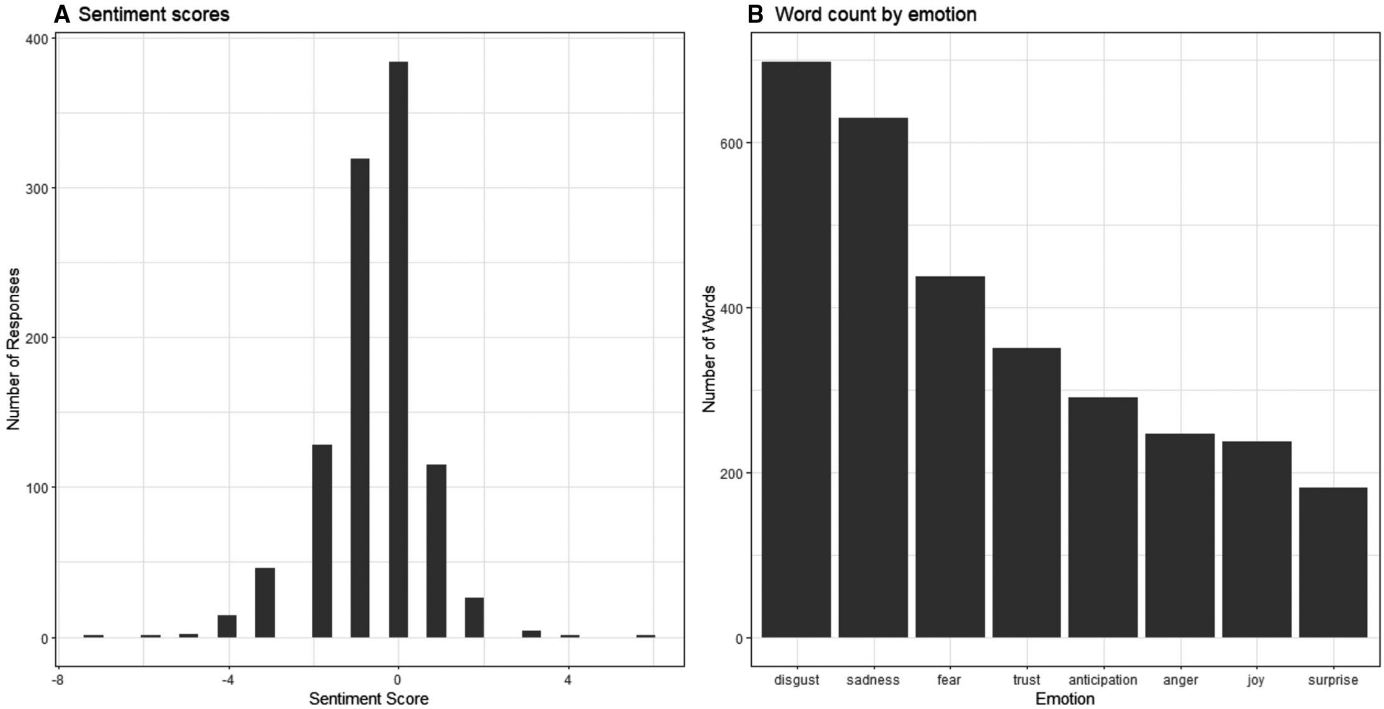

Figure 1 (**A**) Distribution of sentiment, which appears nearly normal. (**B**) Bar chart of the number of words classified in the eight emotion categories of anger, fear, anticipation, trust, surprise, sadness, joy, and disgust. Disgust was the most frequent emotion identified.

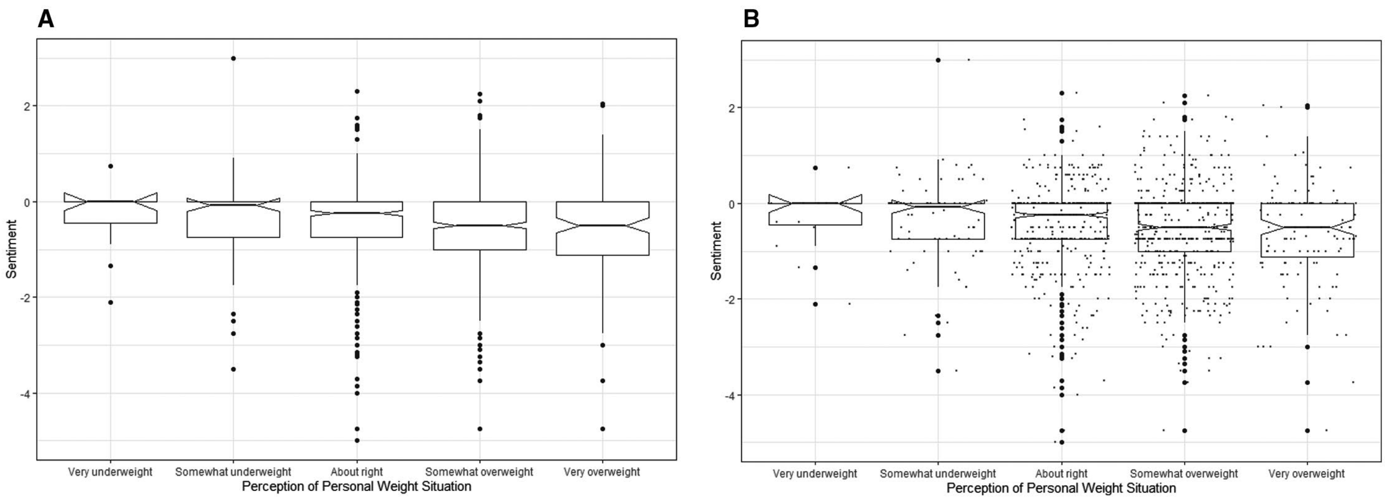

Figure 2 Sentiment for the individual responses to the question "In your opinion, what does the American public think about people with obesity?" was calculated. Higher positive values represent higher positive sentiment, and more negative values represent more negative sentiment. Individual sentiment was partitioned by the participants' response to a weight status Likert-type question (Very Underweight, Somewhat Underweight, About Right, Somewhat Overweight, Very Overweight), and distribution of the sentiment from the free-text response was represented in (**A**) a box plot by perceived weight status. The notches are the size of the 95% CIs. (**B**) Sample size of the distribution of sentiment in each perceived weight status category. Median sentiment and corresponding 95% CIs were lower for individuals who perceived themselves as "Somewhat Overweight" or "Very Overweight."

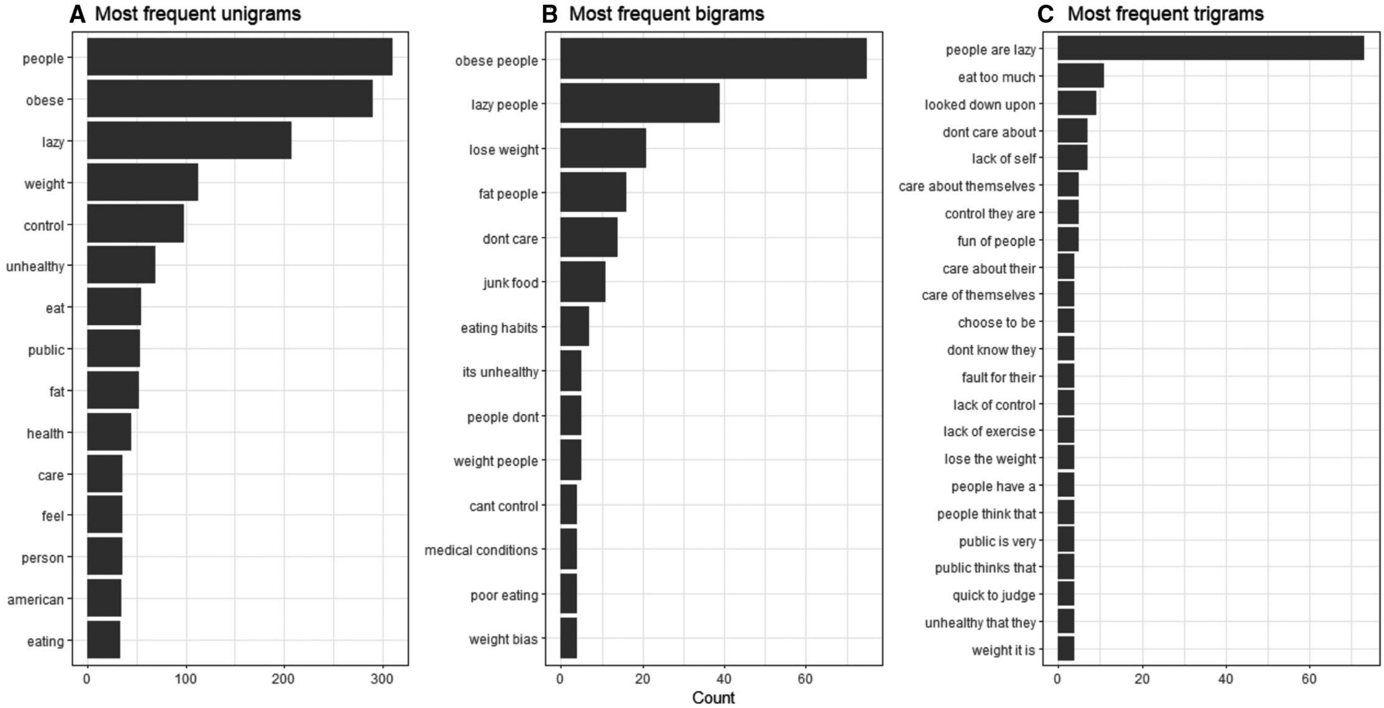

Figure 3 The top (**A**) unigrams, (**B**) bigrams, and (**C**) trigrams obtained in the responses to the question "In your opinion, what does the American public think about people with obesity?" Although some spurious patterns show, the top perceived narrative is people with obesity are lazy.

Discussion

The severity of COVID-19 symptoms in people with obesity has raised the importance of survey research to assess changes to lifestyle during quarantine. Advances in NLP make it possible to analyze free-text responses in large sample sizes. The advantages of including free-text questions is that the participant drives the response as opposed to being guided by a predesigned Likert question. NLP also provides a quantitative objective method to group free-text response in comparison to themes identified by qualitative survey methods.

Here, using free-text responses in a weight bias survey, we demonstrated how NLP can derive insights into sentiment, emotion, and common themes. Similar insights can be obtained from COVID-19 lifestyle surveys, especially when designing questions that can elicit emotion. For example, a two-part question such as "Have you experienced weight gain during quarantine?" followed by "If yes, elaborate on what you think may have contributed to your weight gain" can generate sentiment analysis that identifies how participants genuinely feel. Frequently used phrases can also reveal thoughts that are commonly held by participants. Likert scale questions can be combined with sentiment from free responses to draw insight from survey respondents, as is demonstrated in Figure 2. Additionally, sentiment can be paired with demographic or other Likert data to explain the reasons behind population-wide sentiment (10). Free response text also requires further subjective interpretation. For example, though "people are lazy" was the top trigram that appeared in the free-text response, it appeared 60 times out of a sample size of 1,042 respondents. We do not know whether other respondents may identify with the "people are lazy" narrative but omitted it when they took the survey or whether they disagree with this narrative. In this case, follow-up with focus groups or using the information to design a follow-up Likert scale question would be advisable.

Despite these limitations, NLP, especially combined with Likert scale survey questions, provides deeper insight into what and how participants are thinking about the questions an investigator may want to know about.

Conclusion

Obesity researchers conducting survey research should consider including free-text response questions. The application of NLP makes analysis scalable to large-scale epidemiology research. Free-text response questions can provide rich and unique insights into participants' attitudes, beliefs, and emotions.**O**

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References

1. Sutin AR, Robinson E, Daly M, et al. BMI, weight discrimination, and psychological, behavioral, and interpersonal responses to the coronavirus pandemic. *Obesity (Silver Spring)* 2020;28:1590-1594. doi:10.1002/oby.22914
2. Adams EL, Caccavale LJ, Smith D, Bean MK. Food insecurity, the home food environment, and parent feeding practices in the era of COVID-19. *Obesity (Silver Spring)* 2020;28:2056- 2063. doi:10.1002/oby.22996

3. Di Laura R, Gualtieri P, Pivari F, et al. Eating habits and lifestyle changes during COVID-19 lockdown: an Italian survey. *J Transl Med* 2020;18:229. doi:10.1186/s12967-020-02399-5.
4. Agresti A. *Analysis of Ordinal Categorical Data*. 2nd ed. Hoboken, NJ: Wiley; 2010.
5. Kuzon WM, Kuzon WM, Urbanchek MG, McCabe S. The seven deadly sins of statistical analysis. *Ann Plast Surg* 1996;37:265-272.
6. Guilford JP. *Psychometric Methods*. 2nd ed. New York: McGraw-Hill; 1954.
7. Kumar A, Khan SU, Kalra A. COVID-19 pandemic: a sentiment analysis. *Eur Heart J* 2020; 41:3782-3783. doi:10.1093/eurheartj/ehaa597
8. Porreca A, Scozzari F, Di Nicola M. Using text mining and sentiment analysis to analyse YouTube Italian videos concerning vaccination. *BMC Public Health* 2020;20:259. doi:10.1186/s12889-020-8342-4
9. Silge J, Robinson D. *Text Mining with R: A Tidy Approach*. 1st ed. Bejing; Boston: O'Reilly; 2017.
10. Lindquist J, Peng D, Rochelle S, Turner D, Warshaw M. Effective use of public perceptions in assessments. *The Journal of Defense Modeling and Simulation: Applications, Methodology, Technology* 2019;16:285-295.