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Quantifying Food and Beverage Marketing Exposure Among US Adults: Insights from Facebook Data Donation

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Title: Quantifying Food and Beverage Marketing Exposure Among US Adults: Insights from Facebook Data Donation

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Abstract

As digital media reshape where and how people encounter product marketing, measuring exposure to branded food marketing on platforms like Facebook is essential for public health surveillance and policy. We demonstrate a data-donation approach to quantify paid food and beverage advertising exposure on Facebook over a seven-day period. Among 58 respondents who viewed any Facebook advertisements, 51 (80.3%) saw at least one food or beverage advertisement. Of 607 distinct advertisements coded, 23.7% promoted fast-food restaurants; many promoted products high in free sugars, sodium, or total fats. On days of Facebook use among the respondents, mean exposure to branded food or beverage advertisements was 3.54 per day per person (median=1.25). Users averaged 4.6 days/week of platform use—equating to roughly 847 advertisement exposures per year (median=299). Donated social media data provide a feasible, ethical, platform-specific method to monitor digital food marketing and inform the development of policy aimed at reducing exposure to nutritionally poor products.

Introduction

As social and digital media have permeated the global economy and culture over the past two decades, individuals' media consumption has changed substantially. Traditionally, television has been the predominant source of news and entertainment among youth and adults, and television advertisements have accounted for substantial exposure to food marketing.[1] However, with the rise of social media and digital platforms, recent research indicates a transformation not only in where people encounter food marketing, but also in the diverse and often opaque ways products are promoted—such as through influencer marketing, native advertising (i.e., advertising that bears a similarity to the material that surrounds it online and that may be difficult to identify as advertising), and integrated branded content.[2–4]

Understanding the extent and nature of how companies market their products in the digital media landscape is critical to informing policy development. For example, these changes have important implications for understanding the effects of and monitoring the extent of individuals' exposure to food and non-alcoholic beverage (hereafter referred to as food) marketing and, in turn, how marketing influences food choices and diet-related health risks.

Most studies to date that have examined exposure to food marketing have focused on youth exposure and on broadcast media, such as television. Youth exposure to food marketing is associated with purchase requests and consumption,[5] so it is important to document and monitor exposure to marketing of unhealthy food products to help inform the need for and effective design of policies that can reduce exposure. Earlier studies in the U.S. documented historically high levels of child and adolescent exposure to food marketing on television,[6,7] including on children's programming,[8] demonstrating that industry self-regulation through initiatives such as the Children's Food and Beverage Advertising Initiative (CFBAI) are insufficient to protect children from marketing of unhealthy foods; nor does the CFBAI protect adolescents given that their pledge is limited to children under the age of 13.[9] While several recent studies have found that youth exposure to food marketing on television has fallen over the last two decades,[10–12] this decline coincided with changes in the media environment itself. Moreover, despite declines in both child and adolescent exposure to food marketing on television between 2013-2022, from roughly 5000 to 1000 advertisements seen per year, the majority of advertisements continued to be for unhealthy products.[11,12]

With increases in digital media use, the public health field has begun to examine exposure to food marketing on digital platforms. To date, the gold standard has been to use screen capture methods to obtain objective measures of food marketing content, rather than relying on self-reported measures of exposure.[13] These methods provide

objective, real-time data from a broad range of social and digital media platforms. However, this approach to data collection is highly costly in terms of both time and financial resources and is usually limited to a relatively short time frame of screen capture (generally a range of 15-45 minutes per youth). As a result of the limited time frame, studies with larger sample sizes are needed to understand population averages of exposure, particularly across platforms.

A limited number of screen capture studies focused on youth exposure have been undertaken worldwide to date, and they have consistently found high levels of annual exposure to food marketing across social/digital media platforms: 1560-4067 for 6/7-11-year-olds and 8301-9828 for adolescents 12-16/17 years of age in Canada;[14,15] 8757 for adolescents aged 13-17 in Australia;[16] and, 2461 per year for youth aged 6-19 in Mexico.[17] Additionally, a study focused on YouTube use among 3-8 year olds found that 54% were exposed to food marketing.[18]

Obtaining objective measures of advertising exposure over a longer period of time on different social media platforms can complement information obtained through screen capture methods. Data donation, the process of obtaining social media data from individual social media users, is a potential objective source of marketing exposure data. Ethical data donation leverages users' legal rights to their own data.[19] To our knowledge, no previous study has used detailed platform-specific donated data to examine food advertising content.

Thus, building on the limited literature on digital food marketing exposure, this study is the first to employ a data donation approach, leveraging direct contributions of individuals' social media data to systematically analyze the volume and nature of paid food and beverage advertisements to which they are exposed. Our study focused on adults, but provides unique insights into the digital marketing ecosystem and its implications for public health.

Methods

Recruitment

Participants were recruited via NORC's nationally representative survey panel to voluntarily donate their social media data for research. Data were collected using the AmeriSpeak® Omnibus, a bi-monthly multi-client survey using NORC's probability-based panel designed to be representative of the U.S. household population. Online surveys were conducted between August 8-12, 2024, with adults ages 18 and over representing the 50 states and the District of Columbia; 1,137 completed the survey. Respondents were offered a small monetary incentive for completing the survey.

Omnibus panel members were randomly drawn from NORC's AmeriSpeak panel. Information on the Omnibus survey and AmeriSpeak panel can be found elsewhere in

public documentation.[20,21] The final stage completion rate is 17.0 percent, the weighted household panel recruitment rate is 26.2 percent, and the weighted household panel retention rate is 77.0 percent, for a weighted cumulative response rate of 3.4 percent, all of which were calculated following the official AAPOR guideline.[22]

All 1,137 interviews passed quality assurance checks. A poststratification process was used to adjust for survey nonresponse as well as any noncoverage or under and oversampling resulting from the study-specific sample design. Poststratification variables included age, gender, census division, race/ethnicity, and education. The weighted data reflect the U.S. population of adults ages 18 and over.

Eligibility for Data Donation

All Omnibus respondents were shown a list of popular social media platforms and asked whether they have an account on any platform from the list. Respondents who reported they had either Facebook, Instagram, or both were considered eligible to donate data. Eligible respondents were then shown a screen that explained that NORC is interested in learning more about the effects of social media on society and asking respondents to share their own social media data with NORC for research purposes. A detailed description of the steps involved in data donation was presented. In addition, respondents were assured that all social media data shared with NORC would be stored securely, and any results from analysis would be reported in aggregate, with no personally identifiable information (PII) disclosed.

Opt-in and Consent to Data Donation

After seeing the screen with the description of data donation, all eligible respondents were informed that NORC would provide an additional incentive with a value equivalent to $25 per platform (Facebook and Instagram) as a thank you for their time and contribution of their data. They were then asked, “Are you willing to donate your social media data to NORC?” Willing respondents were next directed to an informed consent module. Respondents who consented were asked to upload their data files to NORC’s secure data donation portal in the next 7 days. At least one reminder email was sent to the respondents who had consented but did not donate their data.

Institutional Review Boards at NORC and the University of Illinois Chicago have reviewed and approved this study and the plans for protecting human subject participants and their data.

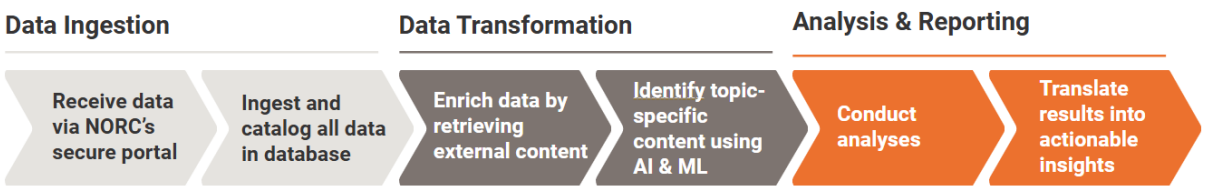
Data Processing

The data provided by Facebook and Instagram to respondents arrived in JSON or HTML format. The process of creating measures from this raw data involved several steps. Figure 1 summarizes our data ingestion, transformation, and analysis pipeline.

First, the data were ingested into a database, in which every interaction, search, and app that respondents used was sorted and cataloged. Files ingested into the database included data on time-stamped views of paid advertisements, along with videos and posts viewed, respondent-specific advertisement targeting, searches conducted, purchases, and other consumer product/media account logins using Meta account credentials.

For this study, we analyzed the Facebook advertisements viewed by each respondent. The files we received contained a mix of text data, including advertiser accounts that posted ads and web addresses pointing to specific content viewed. We enriched the data by retrieving text and images from the linked web addresses. Data processing and enrichment were performed using Python and R.

Figure 1. Data processing pipeline: ingestion, transformation, analysis & reporting.



Classifying Food Advertisements

We operationalized food advertisements as *advertisements that explicitly show or refer to food and beverage products and brands, fast-food and full-service restaurants, food delivery services, meal kits, or food stores within the content*. We identified food advertisements using a multi-stage classification pipeline that combined account-level and content-level signals with expert review. Each advertisement was represented by its advertiser account name, the advertisement text, and a textual summary of visual content derived from image processing (i.e., Optical Character Recognition and object/brand detection). Classification relied on a mix of deterministic keyword matching (used keywords selected by the researchers prior to the study) and model-based assessment to identify food advertising for further review.

Step 1: Account-level screening and model assessment. We first screened advertiser accounts for known food brands and products, curated by subject matter experts, and applied a large language model (LLM)-based assessment when keywords were absent.

Step 2: Content-level screening, model assessment, and expert refinement. For advertisements from accounts that were not clearly identified as food brands or products, we applied keyword-based screening and LLM-based content assessment of

advertisement text and image-derived text/objects. Trained reviewers reviewed samples of classified advertisements to identify systematically missed keywords and to refine deterministic rules; these expert-driven refinements were then applied at the content level.

Step 3: Targeted resolver review for low-confidence or prioritized subsets. A final, targeted review layer re-evaluated selected subsets—including low-confidence cases and advertisements already identified as potential food advertising—using more detailed model prompts and the intermediate outputs from prior steps.[23,24] This resolver stage served both as validation and a consistency check. Because it is more resource-intensive, it was applied only to the aforementioned targeted subsets (roughly 13% of the entire corpus).

Notably, the outputs of the final classifiers, as well as all intermediate LLM classifiers, include not only a binary classification decision ("yes" or "no") but also additional structured information. This information includes an LLM-reported *confidence* score, a brief *rationale* for the classification decision analogous to chain-of-thought explanations,[25] and relevant *extracts* from each advertisement—such as detected brands or products—used both as evidence and guiding information for validation. The confidence score reflects the LLM's verbalized assessment of certainty as elicited by the prompt and has been demonstrated to be a reliable proxy for uncertainty.[26,27] We used the gpt-4o model for each LLM classification using resources available on a dedicated Azure container.

The classifier was developed based on all types of content, i.e., including posts and videos as well as advertisements, although the this study focused exclusively on advertisements. To refine the prompts and tune the components of the classification process, we validated our procedure using random samples of outputs from each stage of the pipeline. Appendix Table B reports the results of this validation based on the final content-level classifications. Overall classification accuracy was 93%, based on a manual review of a random sample of 467 advertisements, posts, and videos. Precision (percent of content correctly classified as food) was 88%, and recall (percent of all instances of food content that were accurately labeled by the classifier) was 91%.

Measurement Creation

Data on advertisements viewed by Facebook users were available for the 7 days preceding data download. For each respondent, we created a measure of the average daily exposure to advertisements on days the respondent used Facebook. The measure was standardized at the advertisement content level to account for differences in observation windows. The observation window was defined as the number of days between the first and last times a person saw any Facebook content in the past (up to) 7 days. We first calculated the total number of times each food advertisement was

viewed (i.e., how many times a person saw a specific advertisement) and divided that by the observation window to derive the average daily exposure to each advertisement per person. This served as the basis for aggregating exposure measures by advertisement type.

Nutritional Content Coding

Facebook advertisements classified as containing food brands or branded products were manually coded by a registered dietician for nutritional content. Using Azure Computer Vision, we identified brand names and food-related text in advertisement images to assist nutrition coding.

Nutrition information for food branded products was obtained through the United States Department of Agriculture's Food Data Central nutrient database and through nutrition facts panels and ingredient lists obtained online. Nutrition information was used to classify foods using the Pan American Health Organization's (PAHO) nutrient profile model (NPM) which is a tool used to identify "unhealthy" foods.[28] The PAHO NPM identifies "unhealthy" food as being processed and ultra-processed food products that are in excess of defined limits of total fat (% calories from total fat ≥30%), saturated fat (% calories from saturated fat ≥10%), trans fat (% calories from trans fat ≥1%), sodium (milligrams of sodium per serving were greater than or equal to the calories per serving), and free sugars (% calories from free sugars ≥10%), and that include the presence of "other sweeteners" (other artificial or natural caloric or non-caloric sweeteners).

Analysis

Facebook food advertisements were coded into the following content categories: beverage, cereal, snacks, sweets, other, fast-food restaurant, full-service restaurant, food delivery service, meal kits/prepared meal delivery, food store, and food brand only. Advertisements were further classified by nutritional content using the PAHO NPM.

For each food content category, we estimated mean and median daily exposure; both measures are reported because daily exposure was right-skewed. For food and beverage product advertisements (not including restaurants, food delivery, food stores or brand only), we additionally calculated the percentage of overall mean exposure that included products that did not meet PAHO NPM limits (e.g., processed and excessive in specific nutrient). All exposure estimates account for survey weights; unweighted estimates are also reported as a sensitivity check.

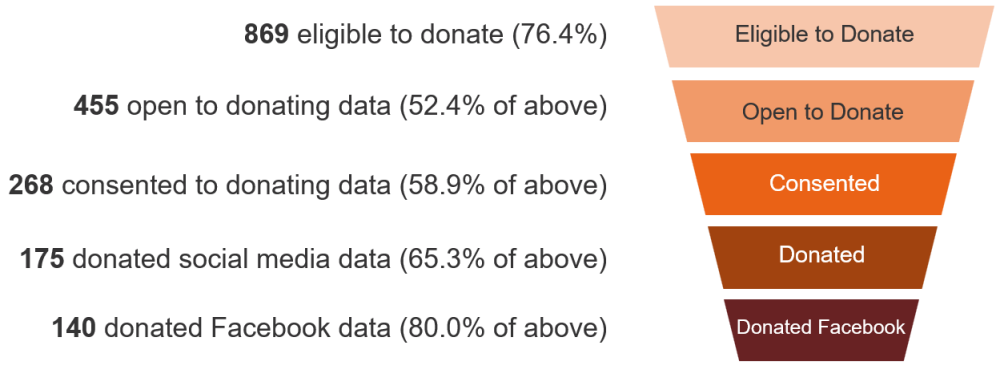
Results

Recruitment

Approximately 76% (N=869) of Omnibus respondents had Facebook and/or Instagram accounts, making them eligible to donate social media data. The top platform was Facebook (70.1%, N=797), followed by Instagram (44.3%, N=504) and YouTube (43.9%, N=499). One in ten (10.7%) reported having no social media account.

As shown in Figure 2, slightly over half of eligible respondents (N=455, 52.4%) stated they would be willing to donate their data. Of those who were willing to donate, nearly 60% (N=268, 58.9%) provided informed consent. Of those who consented, nearly two-thirds retrieved the data from their Instagram and/or Facebook accounts and successfully uploaded those files to NORC's secure data donation portal. Of 175 adults who donated Facebook or Instagram data, 140 donated Facebook data. Of those, 55.7% (N=78) donated the data in a format that could be processed and analyzed. Of those, 74.4% (N=58) viewed at least one ad in the preceding 7 days and are included in this study.

Figure 2. Data donation process flowchart: eligibility, consent, and data donation.



Source: Omnibus on August 8-12, 2024, NORC at the University of Chicago

Because the social media data were obtained within the framework of a nationally representative survey, we compared Facebook data donors who viewed any advertisements on Facebook (N=58) and those who were not exposed to any advertisements (N=20) in the 7 days preceding data donation. Participants who viewed advertisements were similar to those who did not view any advertisements, in that over half were male, over 60% were non-Hispanic White, about 60% had a household

income of $60,000 or more, and more than 85% lived in a metropolitan area. More details are presented in Appendix, Table A.

Content of Food Advertisements

A total of 5,637 advertisements were viewed on Facebook across all participants included in this study. Of those, 796 (14%) were classified as containing food brands or branded products. Five were excluded because no food brand names or food-related text were detected in the advertisement images using Computer Vision. Another 101 were excluded because insufficient information was available to code (e.g., the advertisement image could not be obtained), and 50 were excluded because the advertisements were determined to be unrelated to foods after manual review. Lastly, manual review identified and removed 33 advertisements that were only related to unbranded foods, alcohol, or supplements. As a result, 607 (11% of total food and non-food advertisements) food advertisements were included in this study.

The advertisement content review is summarized in Table 1. Of 607 advertisements, 144 (23.7%) included fast-food restaurants, and 95 (15.6%) included beverage products. The content categories are not mutually exclusive, and one advertisement could be coded for more than one category. The nutritional content analysis was undertaken for 290 (47.8%) food advertisements including the beverage, cereal, snacks, sweets and other product categories and excluding fast-food and full-service restaurants, food delivery, food stores, and brands only.

Table 1. Summary of food or beverage advertisement content by category (N=607)[1]

Advertisement Content Category	n	%
Beverage	95	15.6
Cereal	11	1.8
Snacks	42	6.9
Sweets	60	9.9
Other	103	17.0
Fast-Food Restaurant	144	23.7
Full-Service Restaurant	42	6.9
Food Delivery Service	17	2.8
Meal Kits/Prepared Meal Delivery	86	14.2
Food Store	29	4.8
Food or Beverage Brand only	11	1.8

[1] Numbers and percentages in this table are not mutually exclusive and are not weighted. Counts reflect all unique Facebook food or beverage advertisements viewed by Facebook donors in our sample on the days they used Facebook during the observation window (in the past 7 days prior to their donation).

Exposure to Food Advertisements

Among 58 participants who viewed any Facebook advertisements in the 7 days prior to downloading their data, 51 (80.3%, weighted) had seen at least one food advertisement. Table 2 shows that the average exposure to advertisements with food brands or branded products was 3.54 per day (median=1.25) on days respondents used Facebook. These participants used Facebook for an average of 4.6 days over the prior 7 days. Thus, this exposure level translates to approximately 847 advertisements seen per year (median=299).

The top category of food advertising seen was for fast-food restaurants; those advertisements were viewed by 40 participants (60.9%, weighted) and had an average of 0.79 exposures per day (median=0.28). Table 2 shows the mean and median daily exposure (both unweighted and weighted) to advertisements with food brands or branded products across the 58 participants.

Table 2. Mean and median daily exposure to advertisements with food or beverage brands or branded products (N=58 adults)

Advertisement Content Category	n[1]	%[1]	Daily Exposure (N=58, unweighted)		%[2]	Daily Exposure (N=58, weighted)	
			Mean[1]	Median[1]		Mean[2]	Median[2]
Any food or beverage	51	87.9	4.02	1.46	80.3	3.54	1.25
Beverage	29	50.0	0.67	0.06	48.2	0.59	0
Cereal	9	15.5	0.07	0	17.0	0.06	0
Snacks	17	29.3	0.40	0	32.1	0.34	0
Sweets	20	34.5	0.49	0	35.5	0.44	0
Other	31	53.4	0.81	0.17	52.0	0.70	0.04
Fast-Food Restaurant	40	69.0	0.80	0.50	60.9	0.79	0.28
Full-Service Restaurant	20	34.5	0.25	0	32.5	0.24	0
Food Delivery Service	11	19.0	0.13	0	10.8	0.05	0
Meal Kits/Prepared Meal Delivery	27	46.6	0.39	0	45.1	0.33	0
Food Store	18	31.0	0.14	0	32.0	0.14	0
Food or Beverage Brand only	9	15.5	0.05	0	13.6	0.04	0

[1]Unweighted n, %, mean, median; exposures reflect all Facebook advertisements viewed by Facebook donors in our sample on the days they used Facebook. Note that if an individual views the same content multiple times in a day, each counts as a separate exposure. [2]Weighted %, mean, median.

Nutritional Content of Food Advertising Exposure

After advertisements for restaurants, food delivery, food stores, or brands only were excluded, 41 participants remained who had been exposed to food advertisements. Table 3 shows that under the PAHO nutrition standards, 89.1% of the

average daily exposure to food advertisements was for products that were processed food and excessive in at least one nutrient criterion or contained other sweeteners. Further, 50.0% of the mean daily exposure to food advertisements was for products that were processed and excessive in free sugars. Similarly, 46.1% of the mean daily exposure to food advertisements was for processed food products excessive in total fats. Table 3 also shows corresponding unweighted estimates.

Table 3. Proportion of exposure to food or beverage advertisements that do not meet PAHO nutrient profile model standards (N=41 adults)[1]

	Proportion of mean exposure (based on unweighted data)	Proportion of mean exposure (based on weighted data)
Any food or beverage	100%	100%
Processed food or beverage	93.8%	93.2%
Processed and excessive in at least one nutrient or contains other sweeteners	90.8%	89.1%
Processed and excessive in sodium	46.0%	42.7%
Processed and excessive in free sugars	49.2%	50.0%
Processed and contains other sweeteners	19.0%	17.7%
Processed and excessive in total fats	45.2%	46.1%
Processed and excessive in saturated fats	29.8%	30.8%
Processed and excessive in trans fats	1.9%	1.2%

[1] Nutritional analysis was undertaken for food and beverage product advertisements not including restaurants, food delivery, food stores or brand only.

Discussion

This study demonstrates the feasibility and value of using donated social media data to quantify exposure to paid food advertising in the digital environment. Building on prior work that has relied largely on television audience data or short-duration screen capture methods to measure exposure to advertising, we developed and applied a data donation approach that was embedded in a nationally representative survey of US adults. Our approach allowed us to observe platform-specific advertising exposure over a defined period and to analyze those exposures using systematic content and nutrition coding and ultimately observe exposure levels overall, and by product type and nutritional content.

Our findings indicate that paid food advertising exposure was common among adults who viewed Facebook advertisements during the observation period. Among participants who viewed any Facebook advertisement in the prior 7 days, 80.3% had seen at least one food advertisement, and on average, they saw 3.54 exposures per

day they used Facebook, equivalent to approximately 847 exposures per year if sustained over time. These estimates suggest that paid food marketing on social media represents a substantial source of exposure, even when assessed on only one platform and over a short retrospective window. The distribution of exposure was skewed, as reflected by the lower median exposure estimate (i.e., 1.25 exposures per day that respondents used Facebook), suggesting that some users encounter substantially more food advertising than others. This heterogeneity is consistent with the personalized and algorithmically mediated nature of digital advertising and underscores the need for methods that can assess individual-level variation in exposure rather than relying solely on population-level or aggregated advertising volume.

The nutritional profile of the observed advertising is especially important from a public health perspective. More than 60% of participants who viewed Facebook advertisements were exposed to fast-food restaurant advertisements. Among those exposed to any food or beverage advertisements coded for nutritional content, based on the PAHO nutrient profile, 89.1% of average daily exposure was for processed products that were excessive in at least one nutrient criterion or contained other sweeteners. Exposure was particularly concentrated among products excessive in free sugars, sodium, and total fats. These findings are consistent with the broader literature showing that digital food marketing often promotes products that are inconsistent with dietary recommendations and may reinforce dietary patterns associated with obesity and diet-related chronic disease risk.[14–18] Although the present study focused on adults, the prominence of nutritionally poor products in paid social media advertising raises concern about similar or potentially greater exposure among young people, who are heavy users of digital media and may be especially vulnerable to persuasive marketing.

These results should be interpreted in the context of broader changes in media consumption and marketing regulation. Historically, exposure to paid television advertising has been relatively straightforward to quantify using advertising occurrence data, ratings, and age-specific audience shares, which has made it possible to monitor child-directed marketing and evaluate compliance with self-regulatory pledges. Digital advertising is more difficult to monitor because advertising delivery is individualized, platform-specific, and often inaccessible to researchers. At the same time, children and adolescents increasingly spend time in digital environments, including social media, streaming video, and gaming platforms. Recent evidence indicates that U.S. teens are highly connected online, with YouTube, TikTok, Instagram, and Snapchat widely used, and nearly half of teens reporting that they are online almost constantly.[29]

Our approach is notable because it uses objective data generated through participants' own interactions with Facebook rather than self-reported recall. In doing so, this study provides a proof-of-concept for a scalable measurement framework that complements screen-capture studies. This study is the first to create measures of

exposure to specific types of content using donated social media data. While a recent U.K. study obtained donated TikTok user data for a two-week period from 161 participants to examine TikTok engagement and mental health,[30] and a recent Dutch study with 102 participants analyzed the contents of adolescents' TikTok feeds using hashtag-based topic modeling applied to donated data,[31] to our knowledge, no other studies have directly measured exposure to advertisements or linked exposure with survey respondent characteristics.

A central contribution of this study is the creation of food marketing exposure measures from donated platform data. In addition, our study also demonstrates the utility of a human-in-the-loop classification pipeline that combines deterministic screening, LLM assessment, image-derived text and object detection, and expert review. The final classifier performed well in validation, with high accuracy, precision, and recall (see Appendix), supporting the feasibility of using such pipelines to process large volumes of digital advertising data while retaining expert oversight for ambiguous or high-priority cases.

This study also points to several next steps. First, the data donation approach should be applied to youth samples, including adolescents and, where ethically and legally appropriate, younger children with parental consent. Youth-focused studies are needed because much of the policy concern around food marketing centers on children and adolescents, and because existing industry self-regulatory frameworks do not address adolescents. Second, future work should expand beyond Facebook to other platforms that are more heavily used by youth, including Instagram, TikTok, YouTube, Snapchat, streaming services, and gaming environments. Finally, donated data could be integrated with survey measures, dietary outcomes, and qualitative information about platform use to better understand how advertising exposure relates to attitudes, purchase requests, consumption, and diet-related health outcomes.

Several limitations should be considered. First, although recruitment occurred within a nationally representative survey panel, the analytic sample was small and reflected several stages of selection, including platform eligibility, willingness to donate data, consent, successful retrieval and upload of data, processable file formats, and viewing at least one advertisement during the observation period. If possible, future studies should involve significantly larger representative samples of the population of interest. Second, survey weights were computed for the full Omnibus sample and were not adjusted for the smaller analytic subsamples used in this study. We observed that weighted estimates for exposure levels were broadly similar to unweighted estimates. Third, the observation window was limited to up to 7 days and may not capture variation in advertising exposure over longer periods, seasons, or marketing campaigns. Fourth, donated data depend on the type and completeness of information made available by the platform and successfully retrieved by participants; some advertisements could not

be coded because images or other necessary information were unavailable. Fifth, although the classification pipeline performed well, some misclassification is possible, particularly for ambiguous advertisements, mixed-content advertisements, or advertisements in which food and beverage cues were not captured in text or image-derived features. Sixth, only exposure to paid advertising was assessed, and exposure to owned marketing (e.g., post from a food company showing up organically on a user's feed) and earned marketing (e.g., viral user-generated content featuring branded food product) could also be significant.[32]

Despite these limitations, this study provides an important methodological foundation for monitoring food marketing in digital environments. The results show that donated platform data can be used to identify paid food advertisements, quantify exposure, classify the types of products promoted, and assess nutritional quality using established nutrient profile criteria. As digital media continue to displace or supplement television and other traditional media, public health surveillance will require methods capable of measuring personalized and platform-specific advertising exposure. Screen capture methods remain valuable for observing the full user experience across platforms and for capturing advertising and branded content as it appears in context; donated data, by contrast, can support more intensive analyses of particular platforms and longer observation windows. Data donation offers one promising approach for building this evidence base and for informing policies designed to reduce exposure to marketing for products that may contribute to poor diet quality and diet-related health risks.

Data Availability

The Facebook data supporting this study were collected under informed content provisions that prohibit sharing participants' data. Therefore, the dataset is not publicly available because of ethical and legal restrictions related to participant confidentiality and data protection.

Author Contributions

LP and SE conceptualized and designed the study. SE supervised pilot data collection and analysis. YK supervised development of the data pipeline and led the main data analysis; SB processed and analyzed the donated data as part of this pipeline. All authors contributed to development of the exposure measurement approach. SE and YK wrote the initial draft of the manuscript; LP and JL reviewed and revised it. All authors approved the final version.

Competing Interests

None

Ethics Approval

Institutional Review Boards at NORC and the University of Illinois Chicago have reviewed and approved this study and the plans for protecting human subject participants and their data.

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Appendix

Table A. Adults who viewed Facebook ads (N=58) and those who did not (N=20) in the past week

		Did not view any ads		Viewed ads		
		n	%[1]	n	%[1]	P-value[2]
Gender	Male	11	62.61	34	58.01	0.78
	Female	9	37.39	24	41.99	
Age	18-29	4	37.70	13	32.39	0.73
	30-39	5	13.55	18	25.62	
	40-49	4	17.37	14	21.54	
	50+	7	31.39	13	20.45	
Race/ethnicity	Non-Hispanic White	15	60.71	38	65.07	0.40
	Non-Hispanic Black	2	7.52	4	3.92	
	Other	2	30.96	10	18.01	
	Hispanic	1	0.82	6	13.00	
Education	At most high school graduate	3	39.02	8	21.18	0.22
	Some college	7	17.31	21	27.26	
	Bachelor	7	35.67	14	24.00	
	Post graduate	3	7.99	15	27.56	
Income	<$30,000	7	30.81	10	20.03	0.78
	$30,000-$59,999	4	10.22	12	19.44	
	$60,000-$99,999	5	23.31	18	28.03	
	≥$100,000	4	35.66	18	32.50	
Region	Northeast	3	17.10	8	16.11	0.14
	Midwest	3	9.34	18	22.51	
	South	6	16.82	18	33.35	
	West	8	56.73	14	28.03	
Living in metro	Non-Metro Area	3	14.15	6	6.69	0.34
	Metro Area	17	85.85	52	93.31	
Housing	Owned	11	69.40	35	60.65	0.55
	Rented/other	9	30.60	23	39.35	

[1] Weighted percentage accounting for survey design and sampling

[2] Rao-Scott Chi-square Test for the difference between people who viewed advertisements and those who did not on Facebook. Note that sample sizes are small for several groups, where the power to detect a difference may be inadequate.

Table B. Food and Beverage Content Classification Out-of-Sample Validation

Metric	Interpretation	Value
Accuracy	Percent of content classifications that are correct	92.6%
Precision	Percent of content correctly classified as food and beverage	87.9%
Recall	Percent of food and beverage content correctly classified	91.3%
False Positive Rate	Percent of irrelevant content misclassified as food and beverage	6.6%
False Negative Rate	Percent of food and beverage content not classified	2.5%

Performance metrics are from a random sample of 467 Facebook advertisements, posts, and videos processed by the classification pipeline. The ground truth food and beverage classification (expert-annotated “yes” or “no”) was established via an expert human coder familiar with the definition and criteria.