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"Spring is the best time to lose weight": Evidence that dieting is seasonal and reaches peak intensity during Spring

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Abstract

Does dieting intensify during Spring? Previous research suggests that body dissatisfaction is seasonal and peaks during Summer. Extending these findings to seasonal dieting, we contend that individuals' apprehensions about heightened Summertime body dissatisfaction motivate Springtime dieting. To detect seasonal dieting, we examined the seasonal frequencies of 69 dieting hashtags within a database of 564 million tweets originating from the United States and spanning eight calendar years (2012–19). In total, we detected 624,920 dieting hashtags. Of these, 30% occurred during Spring, 20% during Autumn/Fall, and 25% during each of Summer and Winter. During Spring, there were ~68,000 additional dieting hashtags compared with Autumn/Fall, and ~34,000 additional hashtags compared with Summer and Winter. Of the nine most common dieting hashtags that together accounted for 96% of the total, all nine peaked during Spring (*p*s < .0001). This Spring-centric pattern was apparent for both appearance-oriented diets (e.g., "atkins" and "weightwatchers") and ostensibly *non*-appearance-oriented diets (e.g., "vegan" and "glutenfree"), suggesting that non-appearance-oriented diets might nonetheless be co-opted for appearance-oriented purposes. In conclusion, we found credible evidence that dieting intensifies during Spring. Future research should examine whether eating disorders and muscle dysmorphia also intensify during Spring because dieting is intrinsic to both these conditions.

Keywords: seasonal dieting; dieting; body image; social media; Twitter; big data

Introduction

The term "seasonal dieting" refers to changes in dieting that occur across the Gregorian seasons of Spring, Summer, Autumn, and Winter. We propose that seasonal dieting is characterised by a distinct pattern – dieting that begins and/or intensifies during Spring because individuals anticipate feeling heightened body dissatisfaction during Summer.

A casual Google search reveals that the approach of Summer is a cue for people to start dieting. Consider, for example, the Health.com article "6 reasons Spring is the best time of year to lose weight", which states that "…with Spring underway and Summer on the horizon, you're smack in the middle of the best time of the year to drop pounds" (Health, 2018). As another example, consider the "Emergency Crash Diet & Workout: Shredded for Summer in 21 days" program that informs its reader that "The promise of going shirtless is a powerful motivator. However, all of a sudden, it's roughly one week until Summer. And again, you've waited too long to get your body ready" (TigerFitness, 2018). Finally, consider Weight Watchers, which informs its reader that "Whether you have a holiday coming up or you simply want to feel more comfortable in your Summer clothes, here are some ideas to get you started" and asks rhetorically whether the reader would like to "fit into your favourite bikini on holiday, firm your legs after months in thick tights, or tone your arms to feel confident in your Summer clothes?" (Weight Watchers, 2021b, 2021a). Whilst these examples are focused on weight loss, we believe seasonal dieting also exists in the context of muscle-building. In muscle-building circles, the dietary pattern of "bulking" (eating more calories than required to maintain body weight) during Autumn/Fall and Winter and then "cutting" (eating fewer calories than required) during Spring in preparation for Summer, is ubiquitous. Consider, for example, a male bodybuilding guide which states that "The natural progression of the seasons has given rise to a popular concept in the fitness community: Summer cutting", followed by "useful tips for helping you succeed in losing weight for the Summer without

losing your mind" (AskMen.com, 2016). In summary, we are confident that seasonal dieting is a genuine cultural phenomenon worthy of empirical attention.

The connection of seasonal dieting with seasonal body dissatisfaction

We view seasonal dieting as a consequence of seasonal body dissatisfaction, a closely related term that refers to fluctuation in body dissatisfaction across the seasons (Griffiths et al., 2021). The underlying climactic driver behind seasonal body dissatisfaction is the warmer weather of Summer that compels people to wear fewer layers of clothing together with clothes that expose and accentuate more of the body, such as shorts, skirts, singlets, sleeveless dresses, and swim wear. People also spend more time in places where minimal or revealing clothing is the norm, such as the beach or in swimming pools. To detect and characterise seasonal body dissatisfaction, Griffiths and colleagues examined how sexual minority men felt about their bodies during Spring, Summer, Autumn/Fall, and Winter. A clear pattern emerged for participants residing in both the Northern and Southern Hemispheres: body dissatisfaction was strongest in Summer and weakest in Winter. Moreover, the men reported consistent seasonal differences in four key mechanisms of seasonal body dissatisfaction: pressure from media advertisements, pressure from peers on social media, the feeling that one's body is on public display, and comparisons of one's physical appearance to others' appearances. The effect sizes were mostly medium to large, suggesting these pressures are far from trivial.

Following on, we construe seasonal dieting as a Spring-centric response to past experiences – and expected future experiences – of heightened body dissatisfaction during Summer. We propose that individuals recall past experiences of Summer-centric body dissatisfaction and body image pressures and project these expectations and apprehensions into the future. If this is the case, we would expect to see these expectations, anxieties and apprehensions manifest in various forms, including, in the context of our study, an increased

frequency of dieting tweets during Spring. Detection of seasonal variation in the frequency of dieting-related social media posts would lend credence to the notion of seasonal dieting as a phenomenon and allow for a subsequent empirical evaluation of its characteristics and outcomes, including potential intervention points. Figure 1 visualises the theorised seasonal asynchrony between dieting and body dissatisfaction. In summary, the Figure proposes that dieting peaks during Spring whilst body dissatisfaction peaks during Summer. Whereas Griffiths and colleagues (2021) examined the hypothesised Summer-centric nature of seasonal body dissatisfaction, our study examines the hypothesised Spring-centric nature of seasonal dieting.

Seasonal dieting and eating disorders

Social and cultural phenomena have an outsized impact on eating disorders – a category of psychological disturbance that characteristically involve eating- and appearance-related cognitions and behaviours (American Psychiatric Association, 2013; Anderson-Fye, 2018; Brown & Tiggemann, 2021; Griffiths & Yager, 2019; World Health Organization, 2018). For example, a young woman with anorexia nervosa may dread her upcoming birthday because the cultural expectations surrounding birthdays dictate – or at least make it very likely – that she will be publicly offered birthday cake to eat (Chandiramani, 2016). Whilst this event may sound innocuous and desirable to someone without an eating disorder, an individual with an eating disorder may experience a substantial intensification of their eating disorder symptoms before, during, and/or after their birthday. As another example, a man with muscle dysmorphia who practices the religious fast of Ramadan may experience an intensification of his eating disorder symptoms before, during, and after the fast (Murray et al., 2011).

In contrast to the above-named events, seasonal dieting may represent an intensification of dieting *en masse* (i.e., at the general population level). Spring and Summer are recurrent,

inescapable (unless one flies to the opposite Hemisphere), and long-lasting (three months for each season). In addition, Summer-centric cultural events are often ubiquitous and deeply culturally embedded. For example, in Australia, beaches and beachgoing are celebrated as "symbols of the Australian way of life" (National Museum of Australia, 2021). The lived experiences of individuals with eating disorders and muscle dysmorphia often explicitly refer to Summer-centric activities, such as the beach and swimming pools, where the body is on public display and challenging to conceal (Massiah, 2021; Phillips, 2019; Young, 2019). In her article titled "Coping with 'beach body' season when you have an eating disorder", Young (2019) states that "I wanted to look good in my shirt and clothing. … Being in Summer clothing really intensified that, because of course when it's the Fall and Winter you're more covered up. But when it was Summer I could actually see more of me. It was also when I could find more problem areas to focus my attention on and justify my behaviours." In summary, we believe that the seasonal body image pressures that individuals feel most strongly during Summer are motivating them to diet during Spring. Further, we believe these Spring-centric dieting anxieties and intentions are detectable at an aggregate, general population level, with possible implications for eating disorders.

Study aims and hypotheses

The primary aim of our study was to detect and characterise seasonal dieting. Twitter, a social media platform boasting 206 million daily active users (Statista, 2021), provides a useful opportunity for the detection of seasonal dieting. We believe that individuals' tweets about dieting on Twitter are reasonable proximal reflections of real-world dieting cognitions, intentions, and anxieties. Relatedly, aggregate Twitter posts have been shown to correlate with real-world behaviours in recent research. For example, Blake and colleagues (2021) showed that misogynistic tweets in the United States were correlated with more incidents of domestic and family violence in >400 locales from 2013 to 2014. In brief, we algorithmically

geolocated to the United States several hundred million tweets posted between 2012 and 2019 and then used embedded timestamp data to categorise them into seasons. We subsequently compiled a comprehensive list of diets and dieting hashtags and examined whether there was a Spring-centric pattern of seasonal differences in the frequencies of these hashtags (see Methods for more detail).

Confirmatory hypothesis. Consistent with the theoretical model of seasonal dieting and body dissatisfaction visualised in Figure 1, our confirmatory hypothesis was that the frequency of dieting hashtags would peak during Spring.

Exploratory hypothesis #1: Our first exploratory hypothesis focused on whether seasonal changes in the frequencies of dieting hashtags would differ for appearance-oriented diets versus non-appearance-oriented diets. Our list of dieting hashtags included diets that are explicitly about weight loss, fat loss, and/or appearance modification (e.g., “atkins”) together with diets that are ostensibly about something other than weight loss, fat loss, and/or appearance modification (e.g., “vegan” and “cleaneating”). Our justification for including non-appearance-oriented dieting terms is that these diets, whilst ostensibly not about modifying appearance, may (i) nonetheless mandate dietary restrictions that contribute to weight loss and which – when taken to extremes – are characteristic of eating disorders themselves; and be (ii) marketed and promoted in ways that make clear that body composition changes (e.g., weight loss or building muscle) are goals or “success markers” for the diet.

For example, we believe that some individuals pursue vegetarian and vegan diets not only for reasons of animal welfare and environmental degradation/preservation, but also for reasons to do with modifying their appearance. Vegetarianism and veganism may function as a shield that individuals can use to deflect or defray concerns from others as they pursue goals that, to varying degrees, are appearance-oriented. Consider the following reflections of

an individual who acted as a carer for a person diagnosed with anorexia nervosa: “I am 100% convinced that my daughter’s request to follow a vegan diet was driven by her illness. Through her whole life I ensured that the family had a healthy and balanced diet which included treats and party food. In our house, no food was a “bad” food”. Prior to being diagnosed with anorexia, she first announced that she wanted to cut out meat, then fish then eggs. Within three months she wanted to become vegan… We are now in a good place [after treatment] and she has admitted, guiltily, that she never wanted to be a vegan and her illness drove her to pursue this as a way of restricting” (Fuller et al., 2021, p. 4). Of course, in saying this, we do not wish to cast undue aspersions on the motivations of individuals who are vegetarian, vegan, or otherwise; rather, we are claiming that there is a reasonable probability of there being a sufficient body image signal within these ostensibly non-appearance-oriented dieting terms to make them worthy of examination in our study. Stated differently, we believe a sufficient proportion of these ostensibly non-appearance-oriented diets are driven by appearance-oriented concerns, and therefore, are likely to demonstrate seasonal fluctuations in line with published research on seasonal body image. For more in-depth discussion of the connection of eating disorders with vegetarianism and veganism specifically, we recommend recent work by Heiss, Hormes, and Timko (2017), and Sergentanis and colleagues (2020).

Exploratory hypothesis #2: Our second exploratory hypothesis focused on whether climate parameters, such as cities’ minimum, average, and maximum temperatures, were predictive of dieting hashtag frequency. As mentioned in Griffiths and colleagues (2021), the underlying climactic mechanism of seasonal body dissatisfaction is warmer weather. Although our ability to connect climactic and tweet data was somewhat rudimentary, we nonetheless explored whether climate parameters were predictive of hashtag frequency.

Method

Open science commitment

Aggregated data, code used in our data analyses and data visualisations, and our full list of dieting hashtags, are publicly available on the Open Science Framework: [https://osf.io/sv786/]. We warmly encourage researchers to avail themselves of these resources and welcome requests for clarification.

Measures

Dieting hashtags. We created a list of 194 candidate dieting terms gathered from Twitter, Instagram, Reddit, urban dictionary, Wikipedia, and various online resources explaining dieting jargon. We also relied on our knowledge and expertise of various diets in our capacity as researchers in the field of eating disorders and body image. Ultimately, the list was whittled down to 100 dieting terms, and of these, we detected 69 in our tweet database. The final list of dieting hashtags was broad and included: (i) the overarching term "diet" (N = 322,569 hashtags); (ii) specific diets that were historically popular (e.g., "atkins", N = 9,960); (ii) specific diets that are contemporarily popular (e.g., "paleo", N = 35,965); (iii) "ways" of eating that are dieting nonetheless (e.g., "cleaneating", N = 3,872); (iv) specific diets tied to commercial organisations (e.g., "weightwatchers", N = 2,919); (v) diets that exclude a particular component of food (e.g., "gluten free", N = 22,402); and (vi) diets that exclude a particular category of food (e.g., "vegan", N = 195,173).

Procedure

We searched for tweets containing dieting hashtags within Twitplat, a database of 4.6 billion tweets from the years 2012–19 inclusive. TwitPlat was established and is maintained by the last author with support from the University of Melbourne's Data Analytic Program. The database is composed of tweets streamed from Twitter's Application Programming Interface (API), which provides access to a random sample of publicly available tweets for

each year (anywhere between 1–40% of posts). For this study, our search included tweets geolocated to the United States using a validated tweet geolocation algorithm developed by Blake and colleagues (2018). Of the 4.6 billion tweets in Twitplat, 564 million were geolocated to the United States. We constrained our study to the United States because (i) the country boasts the largest number of Twitter users (73 million; Statista, 2021); and (ii) our analyses required time- and cost-intensive supercomputing resources to conduct. We applied our dieting search terms to Twitplat and extracted 515,815 dieting tweets from the United States between the years 2012 and 2019, each of which contained at least one dieting hashtag. In total, 624,920 dieting hashtags were contained in these tweets. We then used timestamp data embedded within the tweets to categorise them into a season.

Data Analyses

Confirmatory analyses: Do dieting hashtags peak during Spring?

First, we calculated the frequency of each dieting hashtag and the proportion each of these hashtags accounted for across all dieting tweets (see the leftmost columns in Table 1). We then calculated frequencies and proportions for each hashtag stratified by season (see the rightmost columns in Table 1). Subsequently, we conducted a series of chi-square goodness-of-fit tests to determine whether these frequencies differed by season. We then repeated the above-described chi-square analyses for the aggregated dieting hashtags (i.e., all the dieting hashtags in our dataset combined; see the bottom row). Second, and complementary to the above analyses, we conducted a series of negative binomial regressions with Winter, Autumn/Fall, and Summer dummy-coded as predictor variables and the aggregated frequency of dieting hashtags as the dependent variable. In our dummy-coding structure, Spring was coded as the reference group. For reference, negative binomial regressions are the most appropriate analysis when over-dispersed count data are the dependent variables. In this context, “over-dispersed” means data that are considerably more variable than a parametric

model would prescribe, and over-dispersion is common for count/frequency data such as ours. Finally, we included a random intercept for state; meaning, we formally accounted for variation emanating from the state the tweet originated from. Finally, we offset each model by the total number of tweets for that state (i.e., all tweets, not just dieting tweets), allowing our models to account for overall tweet volume. All 50 states plus the District of Columbia were represented.

Exploratory analyses: Is there a difference between appearance-oriented diets and ostensibly non-appearance-oriented diets?

We re-conducted the above-described negative binomial regressions with two different dependent variables in which the aggregated frequency of dieting hashtags was split into (i) appearance-oriented dieting hashtags only, and (ii) non-appearance dieting hashtags only. Authors SG, KB, and TC-C were in complete agreement in classifying each dieting term as being appearance-oriented or non-appearance-oriented. In Table 1, for example, we classified the following dieting terms as representative of non-appearance-oriented diets: “vegan”, “glutenfree”, and “superfood”, and the following terms as representative of appearance-oriented-diets: “atkins”, “weightwatchers”, and “lowcarb”. We excluded “diet” from these analyses because there was no indication as to whether this represents an appearance-oriented or non-appearance-oriented diet. Nonetheless, in the interest of thoroughness, we conducted a regression with just “diet” as the dependent variable.

Exploratory analyses: Do climate parameters predict dieting hashtags?

We conducted a series of negative binomial regressions with a limited set of climate parameters as predictor variables and the frequency of dieting hashtags as the dependent variable. To accomplish this, we extracted the mean minimum, mean average, and mean maximum temperatures for all cities in the United States from the United States Climate Normals, which is a database that provides information about historical climate conditions

(National Centers for Environmental Information, 2021). Importantly, because our tweet dataset contained all tweets geolocated to the United States, but not all tweets are geolocatable to a United States *city*, there were a large minority of tweets that we could not obtain corresponding climate data for (~40%). In effect, this means that the sample size for our exploratory temperature-based regression analyses was substantially smaller than the sample size for our confirmatory season-based regressions, entailing a commensurate reduction in statistical power. Nonetheless, we proceeded with three sets of negative binomial regressions containing (i) mean minimum temperature, (ii) mean maximum temperature, and (iii) mean average temperature as predictor variables, respectively. Simultaneous inclusion of all three variables was inadvisable because these three variables are highly inter-correlated; therefore, we ran the regressions separately. We also conducted these regressions with and without the co-variates of cities' mean age and mean income, which were sourced from the United States Census Bureau. The inclusion of age and income as co-variates were not substantive aspects of the seasonal theory/model; rather, we included these variables because they were readily obtainable city-based data points that could reduce the amount of noise in our analyses by accounting for some of the variation in dieting tweets. Stated differently, we thought younger and more affluent individuals might both tweet more frequently and make more frequent dieting tweets. We mostly did this because we were concerned that these analyses were less well powered than our previous analyses that did not include temperature data. Finally, we tested the suitability of our negative binomial models by comparing them against zero-inflated models, using Akaike information criterion (AIC) values to determine the models to retain.

Sensitivity analyses: Are there seasonal differences in the valence of dieting hashtags?

We wanted to ensure that any seasonal changes in the frequency of dieting hashtags were not confounded by changes in the sentiments of tweets (e.g., "I hate dieting" versus "I

love my new diet!"). We ran a sentiment analysis using an algorithm that detects positively and negatively valenced words and then examined whether the count of diet tweets containing positive and negative words, and the ratio of positive to negative words in diet tweets, differed between the seasons.

Results

Confirmatory analyses: Do dieting hashtags peak during Spring?

As shown in Table 1, a small number of dieting hashtags were over-represented. The most common hashtag, "diet" accounted for approximately half of all dieting hashtags, followed by "vegan", which accounted for approximately one-third. Combined, these two hashtags accounted for 82.4% of our dieting hashtags. The top nine most frequently occurring hashtags, which together accounted for 96.8% of our dieting hashtags, were "diet", "vegan", "paleo", "glutenfree", "atkins", "superfood", "govegan", "cleaneating", and "lowcarb". Continuing with Table 1, we see that the frequencies of these dieting hashtags consistently peaked during Spring. This pattern was present for both of our dominant hashtags, "diet" and "vegan", and for nine of our top 10 hashtags. Of the full list of 19 hashtags shown, 15 occurred most frequently during Spring. Results from our chi-square goodness-of-fit tests indicate that all differences shown in Table 1 are statistically significant, $\chi^2(3)$s > 29.89, ps < .0001. For interested readers, Table 2 contains a brief explanation of each dieting hashtag featured in Table 1.

The results from our negative binomial regression confirmed the Spring-centric pattern observed in our above-described chi-square goodness-of-fit analyses. Examining our dummy-coded predictors, we found that the aggregated frequency of dieting hashtags was higher during Spring than Summer, $b = 0.17$, $SEb = 0.03$, $Z = 6.41$, $p < .0001$, higher during Spring than Autumn/Fall, $b = 0.31$, $SEb = 0.03$, $Z = 11.60$, $p < .0001$, and higher during Spring than Winter, $b = 0.13$, $SEb = 0.03$, $Z = 5.03$, $p < .0001$. We calculated trigamma pseudo R^2

inclusive of both our fixed and random effects for the non-zero-inflated model using the piecewiseSEM package, yielding a value of .084, $\chi^2(3) = 135.78$, $p < .0001$; meaning, the overall regression model was significant.

To help readers better understand our data, we have created three data visuals (see Figures 2–4). Figures 2 and 3 visualise the (i) observed frequencies of dieting hashtags during each month of the year, and (ii) the deviations between the observed frequencies and expected frequencies of dieting hashtags during each month of the year, respectively. Finally, Figure 4 is a geographic heatmap showing seasonal differences in the frequency of dieting hashtags in the various states of the United States. The Figure suggests that the Spring-centric intensification of dieting across the United States is uneven with respect to geography. California, for example, stands out as a state with substantial seasonal intensification of dieting.

Exploratory analyses: Is there a difference between appearance-oriented diets and ostensibly non-appearance-oriented diets?

We observed no substantive differences in the seasonal patterns of appearance-oriented dieting hashtags and non-appearance-oriented dieting hashtags – both reliably peaked during Spring. Looking at the top nine dieting hashtags in Table 1 (accounting for 96.3% of all dieting hashtags), we see that "vegan", "glutenfree", and "superfood" were Spring-centric in the same way as appearance-oriented dieting terms, such as "atkins" and "weightwatchers", and "lowcarb" – as previously stated, all these differences are significant (ps < .0001). Moreover, in our regression models, we again found that dieting hashtags were most frequent during Spring compared to the other three seasons: This was the case for appearance-oriented diets only (bs = 0.14 –0.47, SEbs = 0.050–0.051, Zs = 2.79 –9.13, ps < .005) and non-appearance-oriented diets only (bs = 0.13 –0.30, SEbs = 0.035 –0.035, Zs = 3.73 –8.58, ps < .0002). For completeness, we also note that the Spring-centric pattern was evident when

examining the frequency of just the term "diet" (*b*s = 0.12 –0.28, *SEb*s = 0.027–0.027, *Z*s = 4.31–10.21, *p*s < .0001). In summary, in two sets of analyses focused on individual dieting hashtags and aggregated dieting hashtags, the Spring-centric pattern reliably and consistently emerged for both appearance-oriented and non-appearance-oriented dieting hashtags. Finally, we noted that these results were robust and were extremely unlikely to change if particular diets were re-classified from appearance-oriented to non-appearance-oriented, or vice-versa.

Sensitivity analysis: Are there seasonal differences in the valence of dieting tweets?

As shown in Supplementary Table A, there were no substantive seasonal differences in the mean count of positive words, mean count of negative words, or ratio of positive to negative words. Overall, the sentiment expressed in dieting tweets was mostly positive. Taken together, these results suggest that our analyses were not confounded by a Spring-centric inundation of tweets casting aspersions on dieting.

Exploratory analyses: Do climate parameters predict dieting hashtags?

We successfully geolocated 279,127 dieting hashtags to 4,666 cities of the United States with corresponding climate data. Examining our regression models, we found that cities' mean minimum temperature was positively predictive of aggregate dieting hashtag frequency, $b = 0.17$, $SEb = 0.01$, $Z = 2.19$, $p = .029$. Stated differently, cities with higher/warmer minimum temperatures were predicted to have a higher frequency of dieting hashtags. We note that this finding was contingent on the inclusion of two co-variates in the model: cities' median income level (Z-score standardized), which was positively predictive ($b = 0.32$, $SEb = 0.020$, $Z = 12.98$, $p < .001$), and cities' median age, which was negatively predictive ($b = -0.06$, $SEb = 0.003$, $Z = -16.45$, $p < .001$). In our regression model without co-variates, mean minimum temperature was not significantly predictive of dieting hashtags, $b = 0.09$, $SEb = 0.010$, $Z = 1.27$, $p = .206$. Our regressions containing mean maximum

temperature were non-significant both with and without co-variates (*p*s > .148), as were our regressions containing mean average temperature (*p*s > .285).

Discussion

The aim of our study was to detect and characterise seasonal dieting. To accomplish this, we developed algorithms to extract dieting hashtags within tweets originating from the United States over eight calendar years (2012–19). In line with our theoretical model of seasonal dieting and body dissatisfaction visualised in Figure 1, our primary hypothesis was that the frequency of dieting hashtags would peak during Spring. Exploratory analyses focused on whether seasonal changes in dieting hashtags would be different for explicitly appearance-oriented diets versus ostensibly non-appearance-oriented diets. We further investigated whether certain climate parameters, such as temperature, were predictive of the frequency of dieting hashtags. Finally, we investigated whether there were seasonal changes in the valence/sentiment of dieting tweets.

Seasonal dieting seems to be a genuine and substantive phenomenon

We observed consistent seasonal differences in the frequencies of dieting hashtags with the highest frequencies reliably observed during Spring. As shown in Table 1, when looking at dieting hashtags in aggregate (see the bottom row of the table), we detected 193,281 dieting hashtags during Spring compared with just 125,080 dieting hashtags during Autumn/Fall – a 54% difference equating to an additional 68,201 hashtags. We found that Spring accounted for 30% of all dieting hashtags, Autumn/Fall just 20%, and Summer and Winter each 25%. If seasonal dieting did not exist, we would expect to see each season account for approximately 25% of dieting hashtags. In the context of our study, each 1% difference equates to 6249 hashtags, such that a seemingly modest difference of 5% equates to 31,245 dieting hashtags – a figure we regard as substantive when extrapolating to individuals' dieting anxieties and intentions. These Spring-centric pattern of differences were

significant across two complementary sets of analyses (chi-square-based and regression-based) and survive conservative Type 1 error corrections. Consulting Table 1 again, the Spring-centric pattern was reliably evident when examining individual hashtags. All nine of the most frequently occurring hashtags, which combined accounted for 96.3% of our total hashtags, peaked during Spring. Taken together, we interpret the above as providing support for our primary hypothesis that the frequency of dieting hashtags peaks during Spring.

Theoretical implications: Advancing a seasonal model of body dissatisfaction and dieting

As shown in Figure 1, we construe body dissatisfaction and dieting as phenomena that are influenced by seasonal forces. In this study, we found evidence to support the claim that dieting peaks during Spring, whilst previous research has found evidence to support the claim that body dissatisfaction peaks during Summer (Griffiths et al. 2021). The temporal lag between Spring-centric dieting and Summer-centric body dissatisfaction is theorised to reflect processes wherein individuals recall past experiences of heightened body dissatisfaction during Summer and subsequently anticipating feeling this way during the coming Summer. The warmer months of Spring herald the approach of Summer. Changing body composition through dieting takes time, and so, Spring functions as "the best time to lose weight" so that people can have their body ready for Summer. Griffiths and colleagues found evidence for four potential mechanisms of seasonal body dissatisfaction: appearance-related pressure from media advertising, appearance-related pressure from peers on social media, the feeling that one's body is on public display, and appearance comparisons. We propose that individuals' recollections and anticipations of these Summer-centric pressures motivate Spring-time dieting. Missing still, however, is a direct examination of whether Springtime dieting is motivated by apprehensions about Summertime body dissatisfaction. Quantitative longitudinal and qualitative studies are needed to help us understand how

individuals' dieting anxieties and intentions play out across the seasons. Aside, it is apparent in our study that after Summer there is a waning or relaxation of dieting hashtags during Autumn/Fall. It would be interesting to examine, particularly through qualitative work, whether this corresponds to increased feelings of relief, or perhaps exhaustion, from Springtime dieting and Summertime body anxieties.

We are aware of a study that examined seasonal dieting trends using big data and found results that, at first glance, seem contrary to ours. Park, Wang, and Bulwer (2021) examined Google and Naver (a search engine popular in South Korea) searches for the term "diet" in various countries in the Northern Hemisphere and Southern Hemisphere between 2004 and 2018. Overall, searches for "diet" were lowest in December and January. The authors' interpretation was that the December to January period overlaps the New Year, when people traditionally make New Years' resolutions following the Christmas holidays. If a substantial proportion of these New Years' resolutions focus on losing weight (e.g., Norcross, Mrylako, & Blagys, 2002; Rössner, Hansen, & Rössner, 2011), this will probably flow through to increased diet searches online. Whilst this trend applied to many Anglophone countries (e.g., the United States, Ireland, the United Kingdom, Australia, and New Zealand), the trend was not apparent in predominantly Arab and Muslim countries, where the highest search volumes were in April (the authors acknowledge, however, that only English search terms were examined – the results may differ in the preferred language of these countries were examined). Our interpretation is that, in Anglophone countries, December and January evidence the biggest *difference* in dieting intentions and anxieties. Consulting Figures 2 and 3 in our study, it is evident that the biggest difference is also between December and January – a finding consistent with Park et al. (2021). However, consulting these Figures again, it is also evident that dieting hashtags were more *consistently* elevated in the three months of Spring: March, April and May (Figure 3 shows this pattern especially well). In other words,

the Christmas and New Years period may account for the largest month-to-month *spike* in dieting intentions and anxieties, but Spring accounts for the largest and most consistent season-to-season elevation in dieting intentions and anxieties. Taken together, we view our results and those of Park et al. (2021) as complementary: Our study examined the seasonal model of body dissatisfaction and dieting and found consistently elevated frequencies of dieting hashtags during Spring, and Park et al. focused on the months when diet search terms were at their highest and lowest, finding this to be the December to January period in those Anglophone countries that celebrate Christmas and New Years. Our combined results emphasise the value of research on the social and cultural forces that impact upon body image, dieting, and their clinical manifestations (e.g., eating disorders and muscle dysmorphia), which, as aforementioned, are inclusive of global climactic trends (e.g., the seasons), multi-country eating-related celebrations and holidays (e.g., New Years and Christmas), and innumerable country-, region-, and person-specific celebrations and holidays (e.g., Thanksgiving, Ramadan, and birthdays).

Readers may also have noticed that the frequency of dieting hashtags was lower in Summer than Spring, despite evidence that Summer is when body dissatisfaction is greatest (Griffiths et al. 2021). We propose that individuals start or intensify their dieting in Spring and then most of these diets end or regress within short timeframes. For example, research from the United States on adherence to various diets (e.g., paleo and Weight Watchers) suggested mean adherence durations of between 3 and 5 weeks (Towers et al. 2020). Other diets are meant to last only for a short time (e.g., Whole 30 is intended to last 30 days). In our opinion, these short diets are often particularly restrictive and egregiously promissory about what dieters can achieve in tight timeframes. We propose future researchers use qualitative designs to interrogate how seasonal dieters understand and experience Spring- and Summer-centric body image and eating pressures together with the diets they embark upon.

Finally, to constrain the scope of our study, we conducted only a limited number of exploratory analyses aimed at identifying whether, and to what extent, climate parameters might influence the frequency of dieting hashtags. Here, we observed very limited evidence for the influence of climate parameters and caution readers that this evidence was not robust and was dependent on the inclusion of co-variates; namely, income and age. Nonetheless, the findings provide some direction for future research in the sense that individuals living in warmer cities may be more likely to tweet about dieting. Inhabitants of warmer cities may be more likely to wear clothing that reveals the body over longer periods of a calendar year, potentiating body image and dieting concerns. Aside, our co-variates suggest that cities with younger inhabitants and higher income inhabitants were more likely to tweet about dieting. We caution readers, however, that the above findings are exploratory and speculatory. The connection of underlying climactic conditions to seasonal dieting and body dissatisfaction requires future, dedicated research beyond the scope of our study presented here.

Clinical implication: Are ostensibly non-appearance-oriented diets motivated by appearance concerns?

A striking pattern in our results is that the Spring-centric peaks in dieting hashtags were consistent for both explicitly appearance-oriented diets and ostensibly non-appearance-oriented diets. Stated differently, and as examples: “vegan” behaves the same way as “atkins”, and “glutenfree” behaves the same way as “weightwatchers”. The clinical implication is that diets motivated by concerns about environmental, animal, and personal welfare may nonetheless be partially motivated by the sorts of body image and eating disordered concerns that more clearly drive explicitly appearance-oriented diets. There is a significant tension here – on the one hand, we do not wish to cast unnecessary aspersions on the reasons why individuals pursue diets like veganism and vegetarianism or uncritically contribute to the stigmas of deception and personal responsibility that unjustly plague

individuals with eating disorders (Griffiths et al., 2015a). A recently published and thoughtful commentary by Fuller and colleagues (2021) lays out the dilemma in noting that clinicians' disrespect of these diets may do harm to individuals with eating disorders. However, on the other hand, our results show a clear seasonal pattern to these diets that neatly matches the pattern of appearance-oriented diets, and for which we have no other explanation. Research on veganism and vegetarianism among individuals with eating disorder symptoms and diagnoses suggests there is considerable potential for these diets to be co-opted by eating disordered cognitions, "shielding" the dieter from the concerns of clinicians, parents and peers that would be harder to deflect if the diet were less "defensible", such as atkins or weightwatchers (Zickgraf et al., 2020). The ego-syntonic (aka, positive or desirable) qualities of eating disorders may motivate an individual, consciously or unconsciously, to leverage the moral defensibility of ostensibly non-appearance-oriented diets to achieve body composition changes without attracting scrutiny from others or even oneself (Gregertsen et al., 2017; Griffiths et al., 2015b; Zickgraf et al., 2020). In summary, our results tentatively suggest that, yes, clinicians ought to be compassionately critical of non-appearance rationales for ostensibly non-appearance-oriented diets. We stress the importance of compassion in these critical therapeutic enquiries – a therapeutic alliance will potentially be at risk if critical enquiries are construed as allegations of lying or deceit. For more information pertaining to the above, we recommend that clinicians consult Fuller et al. (2021). For researchers, we recommend an excellent study by Zickgraf et al. (2020).

Beyond veganism and vegetarianism, our Twitter database featured diets that blur the line between appearance-oriented and non-appearance-oriented. For example, "cleaneating" is ostensibly about eating raw, unprocessed foods for the sake of health, but analyses of "cleaneating" social media content reveal a conflation of eating unprocessed food with "health" and achieving and maintaining conspicuous thinness (Walsh & Baker, 2020;

Zemlyanskaya et al., 2021). Dieting of this kind, when taken to extremes that impair an individual's well-being and functioning, is commonplace enough that researchers and clinicians have described it as "orthorexia nervosa" – a proposed eating disorder characterised by the relentless pursuit of extreme dietary purity (see Cena and colleagues [2019] for an informative review). "Cleaneating" was the 8th most common dieting hashtag in our study and evidenced peak frequency during Spring. The clinical implication remains the same: Clinicians should consider making critical and compassionate enquiries into the motivations and origins of clients' ostensibly non-appearance-oriented diets.

Clinical speculation: Might eating disorder symptoms also intensify during Spring?

Seasonal differences in dieting could have clinical implications for eating disorder onset and intensification because dieting is both a risk factor for, and symptom of, eating disorders (Stice et al., 2011). Based on our findings, we speculate that eating disorder symptoms might intensify during Spring and wane during Autumn/Fall. We further speculate that seasonal dieting may entail seasonal intensification of eating disorders *en masse* – that is, intensification at the general population level. If such intensification is indeed occurring, then it may constitute an appreciable public health issue. We also suspect that seasonal dieting may be more intense for individuals with eating disorder symptoms or with risk factors for eating disorder development. For example, in Griffiths and colleagues (2021) study of seasonal body dissatisfaction amongst gay and bisexual men, it was observed that seasonal body dissatisfaction was more intense for men with greater overall body dissatisfaction and for men of higher body weights. Body dissatisfaction and body weight are centrally implicated in eating disorders (American Psychiatric Association, 2013; World Health Organization, 2018), and so, we think it is reasonable to speculate that seasonal dieting may be relatively more intense for individuals with current, or susceptibilities to, eating disorders, over-and-above the general population intensification of seasonal dieting observed in our

study. Stated differently, if you are, for example, a person in a larger body who is already worried about how you look, then the Springtime stressors of getting "beach body ready" and "shredded for Summer" may be particularly strongly felt. We stress to readers, however, that the above are speculations requiring future research.

Fortuitously, an examination of the above-proposed seasonal changes in eating disorder symptoms may be relatively straightforward through collaboration between eating disorders researchers possessing historical datasets. Multiple longitudinal (or even cross-sectional) datasets containing widely used self-report questionnaires of eating disorder symptoms exist and could be merged and analysed to determine whether, and to what extent, eating disorder symptoms fluctuate in a seasonal fashion. With sensible theorising, we may observe not only the above-proposed seasonal differences in eating disorder symptoms, but also potential fluctuations around social or cultural events, such as Christmas, Thanksgiving, or Ramadan (to name but a few). An examination of eating disorder helpline data would also prove useful – if helplines in both the Northern and Southern Hemisphere show a pattern of higher call volume during Spring, then this would provide strong evidence for seasonal intensification of dieting.

Study limitations

Our study is limited in several ways. First, our data are not within-persons or longitudinal. We are only able to conclude that the frequency of dieting hashtags is different *between* seasons and highest during Spring, but this is not the same as concluding that the frequency of diet hashtags *increases* during Spring (though this is the obvious implication). To conclude this, we would have to examine whether individual Twitter accounts change their diet hashtag frequency over time, and an undertaking of this kind is not possible with our current data and algorithms. Following on, we are able to comment only on aggregate behaviour, not individual behaviour – the latter requires future research.

Second, it is possible that confounding variables may account for some of our observed seasonal changes in dieting hashtags. For example, it is possible that dieting in the United States intensifies around idiosyncratic social and cultural events that occur during Spring (e.g., Spring Break). As was done in Griffiths and colleagues (2021), a credible defence against this possibility would require an examination of seasonal dieting in both the Northern and Southern Hemisphere – the inversion of the seasons means that observing an identical Spring-centric pattern in both Hemispheres would credibly refute the influences of and social and cultural events idiosyncratic to Spring in the United States. We note that in Griffiths et al. (2021) the Summer-centric pattern of body dissatisfaction was identical in both Hemispheres, and given this, we are reasonably confident that Spring-centric dieting will emerge in both Hemispheres too. Another potential confounder to consider is that corporations may intensify their diet advertising on Twitter during Spring, causing a spike in the frequency of dieting hashtags that is not driven by individuals per se. Arguing against this alternative explanation, however, are our findings that the Spring-centric peaks is consistent across a broad swathe of diet hashtags, including both hashtags that are clearly corporation-defined/driven (e.g., "weightwatchers") and hashtags that are not corporation-driven/defined (e.g., "vegan").

Third, Twitter uses are not representative of the United States general population. For example, Twitter users tend to be younger, more highly educated, have higher incomes, and are more likely to identify as Democrats (Pew Research Center, 2019). Moreover, the median Twitter user tweets just twice each month compared to a small minority of users who tweet prolifically; for example, the top 10% of active Twitter users account for 80% of all tweets originating from the United States (Pew Research Center, 2019). Therefore, our Spring-centric pattern of seasonal dieting is most relevant to these individuals, and whether this pattern generalises to demographics (and countries) under-represented or not represented in our data is a question requiring future research. Beyond Spring, there are myriad country-

specific events and holidays that focus directly or largely on food, and which may intensify dieting and body dissatisfaction: Thanksgiving in North America, Chuseok in South Korea, Sukkot in Israel, Tsiknopempti in Greece, and Chinese New Year. This list is not exhaustive and comes with the caveat that research on whether these events intensify disordered eating is often equivocal (e.g., for Ramadan; Akgül et al., 2014; Chia et al., 2018). Future research beyond Twitter users and the United States is desirable.

Fourth, we used a definition of Spring based on time. We categorised a tweet as occurring during Spring if it was tweeted during the Springtime months of March, April, and May. We felt this was sensible but acknowledge that certain locales in the United States experience early or late Springs; meaning, the weather starts warming up in late Autumn (e.g., in Florida) or only at the end of Spring (e.g., in Maine). Future research might consider examining seasonal dieting and body dissatisfaction in a more geographically constrained locale (e.g., a town or city) that uniformly experiences seasons that temporally accord with time-based definitions of Spring (i.e., Spring is not late or early) together with substantial seasonal variation in temperatures (i.e., unequivocally hot Summers and cold Winters).

Conclusion

In conclusion, we found credible evidence that dieting is seasonal and reaches peak intensity during Spring. Drawing upon a theoretical model of seasonal dieting and body dissatisfaction, we surmised that individuals' apprehensions about heightened Summertime body dissatisfaction would motivate Springtime dieting, leading us to hypothesise that the frequency of dieting hashtags on Twitter would peak during Spring. Leveraging a multi-year database of several hundred million tweets originated from the United States between 2012 and 2019, we detected 624,920 dieting hashtags and found that Spring accounted for 30%, Autumn/Fall just 20%, and Summer and Winter each 25%. Of the top nine most frequent dieting hashtags that together accounted for 96% of our total dieting hashtags, all nine peaked

during Spring. This Spring-centric pattern was consistent for both appearance-oriented diets (e.g., “weightwatchers”, “atkins”, and “lowcarb”) and *non*-appearance-oriented diets (e.g., “vegan”, “glutenfree”, and “superfood”), implying these latter diets may be co-opted for appearance-oriented purposes to at least some extent. We speculate that eating disorder symptoms may also intensify during Spring and encourage future research into potential seasonal influences on eating disorder symptoms.

References

Akgül, S., Derman, O., & Kanbur, N. Ö. (2014). Fasting during ramadan: A religious factor as a possible trigger or exacerbator for eating disorders in adolescents. *International Journal of Eating Disorders*, *47*(8), 905–910. https://doi.org/10.1002/eat.22255

American Psychiatric Association. (2013). *Diagnostic and Statistical Manual Of Mental Disorders (DSM-5)* (5th ed.)

Anderson-Fye, E. R. (2018). Cultural influences on body image and eating disorders. In *The Oxford Handbook of Eating Disorders, 2nd ed* (pp. 187–208). Oxford University Press.

AskMen.com. (2016). *Summer Cutting Guide: How To Get Your Body Summer-Ready Without Losing Your Mind*. https://www.askmen.com/sports/bodybuilding/summer-cutting-guide.html

Blake, K. R., O'Dean, S. M., Lian, J., & Denson, T. F. (2021). Misogynistic tweets correlate with violence against women. *Psychological Science*, *32*, 315–325. https://doi.org/10.1177/0956797620968529

Brown, Z., & Tiggemann, M. (2021). Celebrity influence on body image and eating disorders: A review. *Journal of Health Psychology*, 1359105320988312. https://doi.org/10.1177/1359105320988312

Cena, H., Barthels, F., Cuzzolaro, M., Bratman, S., Brytek-Matera, A., Dunn, T., Varga, M., Missbach, B., & Donini, L. M. (2019). Definition and diagnostic criteria for orthorexia nervosa: A narrative review of the literature. *Eating and Weight Disorders*, *24*, 209–246. https://doi.org/10.1007/s40519-018-0606-y

Chandiramani, R. (2016). Facing my birthday cake with an eating disorder. The Mighty. http://themighty.com/2016/08/eating-birthday-cake-when-battling-an-eating-disorder/

Chia, J. L. P., Fuller-Tyszkiewicz, M., Buck, K., Chamari, K., Richardson, B., & Krug, I. (2018). An ecological momentary assessment of the effect of fasting during Ramadan

on disordered eating behaviors. *Appetite*, *127*, 44–51. https://doi.org/10.1016/j.appet.2018.04.017

Fuller, S. J., Brown, A., Rowley, J., & Elliott-Archer, J. (2021). Veganism and eating disorders: Assessment and management considerations. *BJPsych Bulletin*, 1–5. https://doi.org/10.1192/bjb.2021.37

Gregertsen, E. C., Mandy, W., & Serpell, L. (2017). The egosyntonic nature of anorexia: an impediment to recovery in anorexia nervosa treatment. *Frontiers in Psychology*, *8*, 2273. https://doi.org/10.3389/fpsyg.2017.02273

Griffiths, S., Austen, E., Krug, I., & Blake, K. (2021). Beach body ready? Shredding for summer? A first look at "seasonal body image". *Body Image*, *37*, 269–281. https://doi.org/10.1016/j.bodyim.2021.03.004

Griffiths, S., Mond, J. M., Murray, S. B., & Touyz, S. (2015a). The prevalence and adverse associations of stigmatization in people with eating disorders. *International Journal of Eating Disorders*, *48*, 767–74. doi:10.1002/eat.22353

Griffiths, S., Mond, J. M., Murray, S. B., & Touyz, S. (2015b). Positive beliefs about anorexia nervosa and muscle dysmorphia are associated with eating disorder symptomatology. *Australian and New Zealand Journal of Psychiatry*, *49*, 812–820. https://doi.org/10.1177/0004867415572412

Griffiths, S., & Yager, Z. (2019). Gender, embodiment, and eating disorders. *Journal of Adolescent Health*, *64*, 425–426. https://doi.org/10.1016/j.jadohealth.2019.01.016

Health. (2018). 6 Reasons Spring Is the Best Time of Year to Lose Weight. *https://www.health.com/weight-loss/spring-weight-loss*.

Heiss, S., Hormes, J. M., & Alix Timko, C. (2017). Vegetarianism and Eating Disorders. In F. Mariotti (Ed.), *Vegetarian and Plant-Based Diets in Health and Disease Prevention* (pp. 51–69). Academic Press. https://doi.org/10.1016/B978-0-12-803968-7.00004-6

Massiah, S. (2021). I was the “fat friend”—& it took me two decades to finally accept my body. *Refinery 29*. https://www.refinery29.com/en-us/body-image-swimsuit-summer-essay

Murray, S. B., Rieger, E., & Touyz, S. W. (2011). Muscle dysmorphia symptomatology during a period of religious fasting: A case report. *European Eating Disorders Review, 19*, 162–168. https://doi.org/10.1002/erv.1016

National Centers for Environmental Information. (2021). *U.S. Climate Normals*. National Centers for Environmental Information (NCEI). http://www.ncei.noaa.gov/products/land-based-station/us-climate-normals

National Museum of Australia. (2021). Discovering the beach. *Https://Www.Nma.Gov.Au/Exhibitions/between-the-Flags/Discovering-Beach*.

Norcross, J. C., Mrykalo, M. S., & Blagys, M. D. (2002). Auld lang syne: success predictors, change processes, and self-reported outcomes of New Year's resolvers and nonresolvers. *Journal of Clinical Psychology*, *58*, 397-405. doi:10.1002/jclp.1151

Pew Research Center. (2019, April 24). How twitter users compare to the general public. *Pew Research Center: Internet, Science & Tech*. https://www.pewresearch.org/internet/2019/04/24/sizing-up-twitter-users/

Phillips, K. (2019). Beach body tyranny hurts men too. *New York Times*, *https://www.nytimes.com/2019/08/29/opinion/sunday/beach-body-tyranny-hurts-men-too.html*.

Rössner, S. M., Hansen, J. K., & Rössner, S. (2011). New Year's resolutions to lose weight--dreams and reality. *Obesity Facts*, *4*, 3-5. doi:10.1159/000324861

Sergentanis, T. N., Chelmi, M.-E., Liampas, A., Yfanti, C.-M., Panagouli, E., Vlachopapadopoulou, E., Michalacos, S., Bacopoulou, F., Psaltopoulou, T., & Tsitsika,

A. (2020). Vegetarian diets and eating disorders in adolescents and young adults: A systematic review. *Children*, *8*, 12. https://doi.org/10.3390/children8010012

Statista. (2021). Leading countries based on number of Twitter users as of July 2021. Statista. https://www.statista.com/statistics/242606/number-of-active-twitter-users-in-selected-countries/

Stice, E., Marti, C. N., & Durant, S. (2011). Risk factors for onset of eating disorders: Evidence of multiple risk pathways from an 8-year prospective study. *Behaviour Research and Therapy*, *49*, 622–627. https://doi.org/10.1016/j.brat.2011.06.009

TigerFitness. (2018). Emergency crash diet & workout: Shredded for summer in 21 days. *Https://Www.Tigerfitness.Com/Blogs/Workouts/Emergency-Crash-Diet-Workout-Shredded-Summer*.

Walsh, M. J., & Baker, S. A. (2020). Clean eating and Instagram: Purity, defilement, and the idealization of food. *Food, Culture & Society*, *23*, 570–588. https://doi.org/10.1080/15528014.2020.1806636

Weight Watchers. (2021a). Summer's here! 10 expert tips for getting active. *Https://Www.Weightwatchers.Com/Uk/Article/Lose-Weight-for-Summer-Fitness-Tips*.

Weight Watchers. (2021b). Summer's here! 10 simple steps to weight loss and body confidence. *Https://Www.Weightwatchers.Com/Uk/Article/Summer-Weight-Loss-Body-Confidence*.

World Health Organization. (2018). *International Classification of Diseases For Mortality and Morbidity Statistics (ICD-11)* (11th ed.).

Young, L. (2019). Coping with 'beach body' season when you have an eating disorder. *Global News*. https://globalnews.ca/news/5388084/eating-disorders-summer/

Zemlyanskaya, Y., Valente, M., & Syurina, E. V. (2021). Orthorexia nervosa and Instagram: Exploring the Russian-speaking conversation around #орторексия. *Eating and Weight*

Disorders - Studies on Anorexia, Bulimia and Obesity. https://doi.org/10.1007/s40519-021-01230-4

Zickgraf, H. F., Hazzard, V. M., O'Connor, S. M., Simone, M., Williams-Kerver, G. A., Anderson, L. M., & Lipson, S. K. (2020). Examining vegetarianism, weight motivations, and eating disorder psychopathology among college students. *International Journal of Eating Disorders*, *53*, 1506–1514. https://doi.org/10.1002/eat.23335

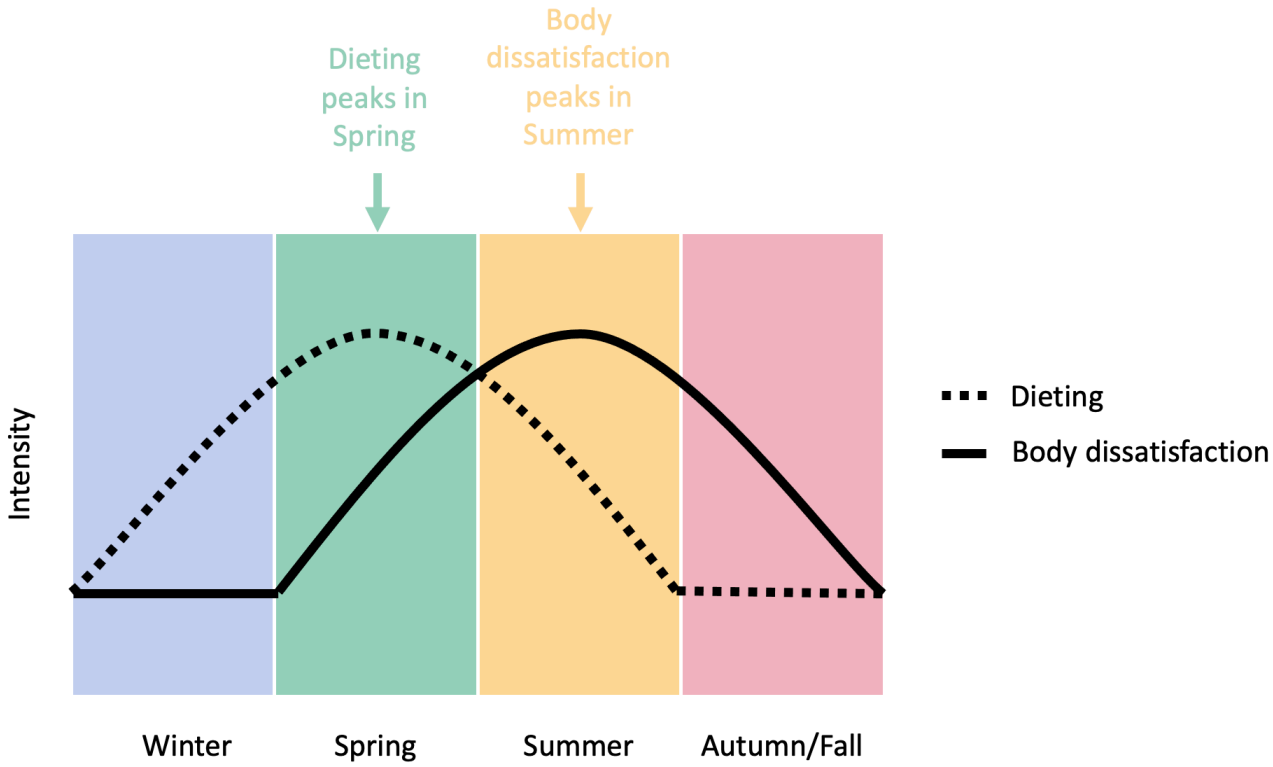

Figure 1. A visualisation of the seasonal asynchrony between dieting and body dissatisfaction. Past research has shown that seasonal body dissatisfaction intensifies in Summer. Based on our conjecture that individuals recall their past experiences of heightened Summer-centric body dissatisfaction and subsequently incorporate these expectations into projections of future Summer-centric body dissatisfaction, we predict an intensification of dieting activity during Spring – a time period that heralds the approach of Summer. Stated more colloquially, people diet during Spring to "prepare" their bodies for Summer. In this sense, there is a temporal discordance between seasonal body dissatisfaction, which peaks in Summer, and seasonal dieting, which peaks in Spring. In our study, we have formally examined the former claim: that dieting intensifies and peaks during Spring.

Table 1. Descriptive statistics for a subset of the hashtags that constituted our dieting hashtags. The 19 hashtags shown here account for a combined 99.45% of the total dieting hashtags and are presented in descending sequential order of frequency. The season with the highest frequency and proportion is **bolded**. See our supplementary material on the Open Science Framework for descriptive data for all 69 hashtags.

Hashtag	All seasons			Season-specific[a]							
				Autumn/Fall		Winter		Spring		Summer	
	N	%[b]	%[c]	N	%[d]	N	%[d]	N	%[d]	N	%[d]
diet	322569	51.34	51.34	65430	20.28	82302	25.51	**97329**	**30.17**	77508	24.02
vegan	195173	31.06	82.40	37374	19.15	47935	24.56	**58601**	**30.00**	51263	26.26
paleo	35956	5.72	88.12	7983	22.20	10030	27.90	**10075**	**28.02**	7868	21.88
glutenfree	22402	3.57	91.69	4986	22.26	5205	23.23	**7004**	**31.27**	5207	23.24
atkins	9960	1.59	93.28	1809	18.16	2016	20.24	**3922**	**39.02**	2213	22.21
superfood	6426	1.02	94.30	1347	20.96	1704	26.51	**1809**	**28.15**	1704	26.51
govegan	5236	0.83	95.13	908	17.34	5205	23.23	**7004**	**31.37**	5207	23.24
cleaneating	3872	0.62	95.75	764	19.73	1001	25.85	**1198**	**30.94**	909	23.48
lowcarb	3397	0.54	96.29	656	19.31	840	24.72	**1071**	**31.53**	830	24.43
whole30	3380	0.54	96.83	467	13.81	**1369**	**40.50**	908	26.86	636	18.81
nutrisystem	3288	0.52	97.35	534	16.24	824	25.06	**1129**	**34.33**	801	24.36
weightwatchers	2919	0.46	97.81	624	21.38	**885**	**30.32**	780	26.73	630	21.58
ketogenic	2900	0.46	98.27	527	18.17	747	25.76	**858**	**29.59**	768	26.48
pegan	2133	0.34	98.61	478	22.41	434	20.34	**611**	**28.65**	610	28.60
lchf	1552	0.25	98.86	297	19.13	405	26.10	413	26.61	**437**	**28.16**
ketosis	1369	0.22	99.08	266	19.43	320	23.37	**435**	**31.78**	348	25.42
vegetarianism	1139	0.18	99.26	**376**	**33.01**	215	18.88	257	22.56	291	25.55
iifym	659	0.10	99.36	132	20.03	145	22.00	**197**	**29.89**	185	28.07
fodmap	590	0.09	99.45	122	20.68	137	23.22	**220**	**37.29**	111	0.19
Totals	624,920	99.45	99.45	125,080	20.02	161,719	25.88	**193,281**	**31.01**	157,426	25.21

Notes: [a] All differences are statistically significant, $\chi^2(3)$s > 29.89, *p*s < .0001
[b] These percentages represent the proportion of the hashtag relative to *all other hashtags*. For example, "diet" represented 51.34% of all detected dieting hashtags.
[c] These are cumulative percentages
[d] These percentages represent the *season-specific proportion* for that specific term. For example, 20.28% of all instances of "diet" occurred during Autumn/Fall whilst 30.17% occurred during Spring.

Table 2. Full names and explainers for each of the dieting hashtags referred to in Table 1

Dieting hashtag	Full name of the diet	Explainer
Vegan / govegan	Vegan	Vegan diets exclude animal products, including meat, eggs, dairy, and honey. Vegan dieters may refer to themselves as dietary vegans or strict vegetarians.
paleo	Paleolithic	Paleolithic or paleo diets, also referred to as caveman diets or stone-age diets, prescribe adherents to consume the same foods that were eaten by humans during the Paleoliethic era (roughly 2.5 million years ago to 10,000 B.C. [Before Christ]). Paleo diets emphasise meat, vegetables, nuts, fruits, and roots. Excluded foods include dairy, grains, sugars, legumes, processed oils, salt, alcohol, and coffee.
glutenfree	Gluten free	Gluten free diets exclude gluten, a protein found in wheat, barley, rye, and triticale. Gluten free diets are prescribed to individuals with coeliac disease, an autoimmune disorder whereby gluten triggers immune responses that damage the lining of the small intestine. Gluten free diets are also popular among individuals with other gluten-related medical conditions, including non-coeliac gluten sensitivity, gluten ataxia, and wheat allergies.
atkins	Atkins	Atkins is a low carbohydrate diet developed in the 1960s by Robert Atkins, a United States doctor. The Atkins diets restricts carbohydrates, especially simple and processed carbohydrates like sugar and white flour, and encourages eating more protein and fat.
superfood	Superfoods	A superfood is defined as "a food that is rich in compounds (e.g., antioxidants) considered beneficial to a person's health". In our (and others') opinion, superfood is often employed as a marketing term that pedestalises certain foods (e.g., blueberries) for having exceptional nutrient density and concomitant health benefits.
cleaneating	Clean eating	Clean eating is a diet or way of eating that emphasises unprocessed, "real", clean foods that are as close to their natural state as possible. Clean eating emphasises fruits, vegetables, and drinking water. Restricted foods include refined carbohydrates (e.g., white bread), oils produced by chemical extraction (e.g, olive oil), added sugar, and alcohol.
lowcarb	Low carbohydrate	Low carbohydrate diets restrict carbohydrates. Atkins and keto are two examples of low carbohydrate diets.
whole30	Whole 30 program	Whole30 is a diet that emphasises whole, unprocessed, "real" foods. Foods that are processed and/or have complex ingredient lists are excluded. Some additional rules include no added sugar (including both real and artificial sugar), no grains, no alcohol (including cooking alcohol), no dairy, and (mostly) no legumes.
nutrisystem	Nutrisystem	Nutrisystem is a company headquartered in the United States that offers a variety of weight loss diets, products, and services.
weightwatchers	Weight watchers	WW International, formerly called Weight Watchers, is a company headquartered in the United States that offers a variety of weight loss diets, products, and services.
ketogenic / ketosis	Keto	Keto or ketogenic diets restrict carbohydrates whilst increasing fat intake. The goal is to shift the body's metabolism away from burning carbohydrates for energy and toward burning fat and ketones. When the body does not have enough insulin to turn glucose – a simple carbohydrate – into energy, the liver turns fat into ketones, which act as an alternate energy source. Carbohydrate restriction in keto is typically more drastic than in Atkins.

pegan	Pegan	Pegan is a vegetarian-forward diet in which the majority of one's diet consists of plant-based food with a minority consisting of animal-based food.
lchf	Low carbohydrate, high fat	Lchf diets are similar to keto diets but typically have a higher carbohydrate allowance.
vegetarianism	Vegetarian	Vegetarian diets exclude meat and by-products of animal slaughter.
iifym	If it fits your macros	Iifym dieters choose a macro-nutrient split (e.g., 40% carbs, 20% protein, 20% fats). So long as these targets are met, the dieter can eat whatever they want. iifym diets are particularly popular with bodybuilders.
fodmap	Low FODMAP	Low FODMAP is a diet that restricts high FODMAP foods. FODMAP stands for fementable oligosaccharides, disaccharides, monosaccharides and polyols. Examples of high FODMAP foods include garlic, onion, apples, processed meats, honey, wheat, rye, and barley.

Note: These pithy diet explainers reflect our understanding of the common tenants of these diets. We acknowledge the considerable heterogeneity within each diet and its adherents. For example: "classic keto" and "dirty keto", "primal paleo", "normal/classic paleo", and "strict paleo", and "dietary vegan", "whole food vegan", "raw-food vegan", "religious vegan", and "ethical vegan". An exhaustive summary of this heterogeneity is beyond the scope of this manuscript.

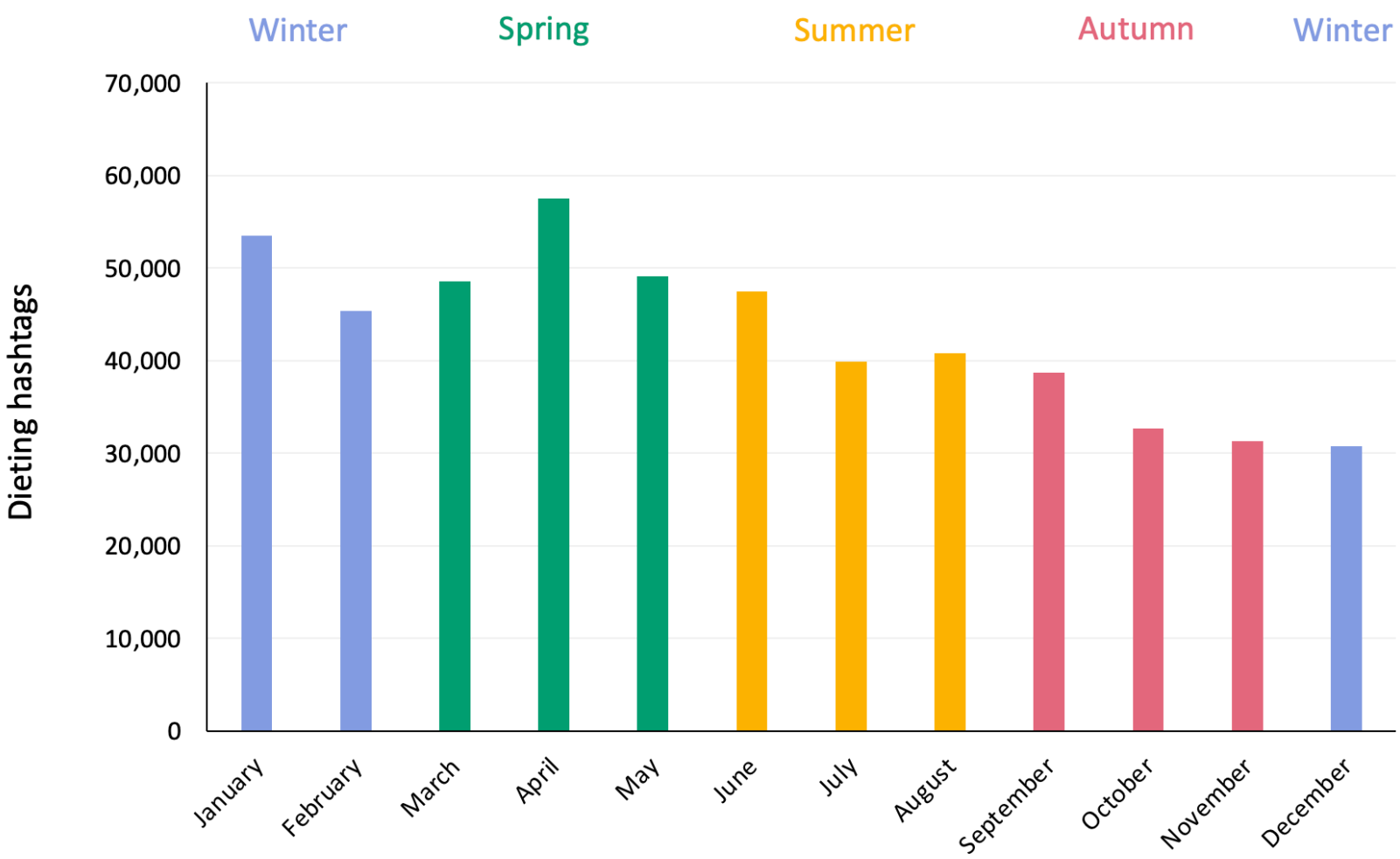

Figure 2. A visualisation of the frequency of dieting hashtags detected during Winter, Spring, Summer, and Autumn/Fall in the United States between 2012 and 2019. Confidence intervals for each column are extremely small and do not appear on the figure.

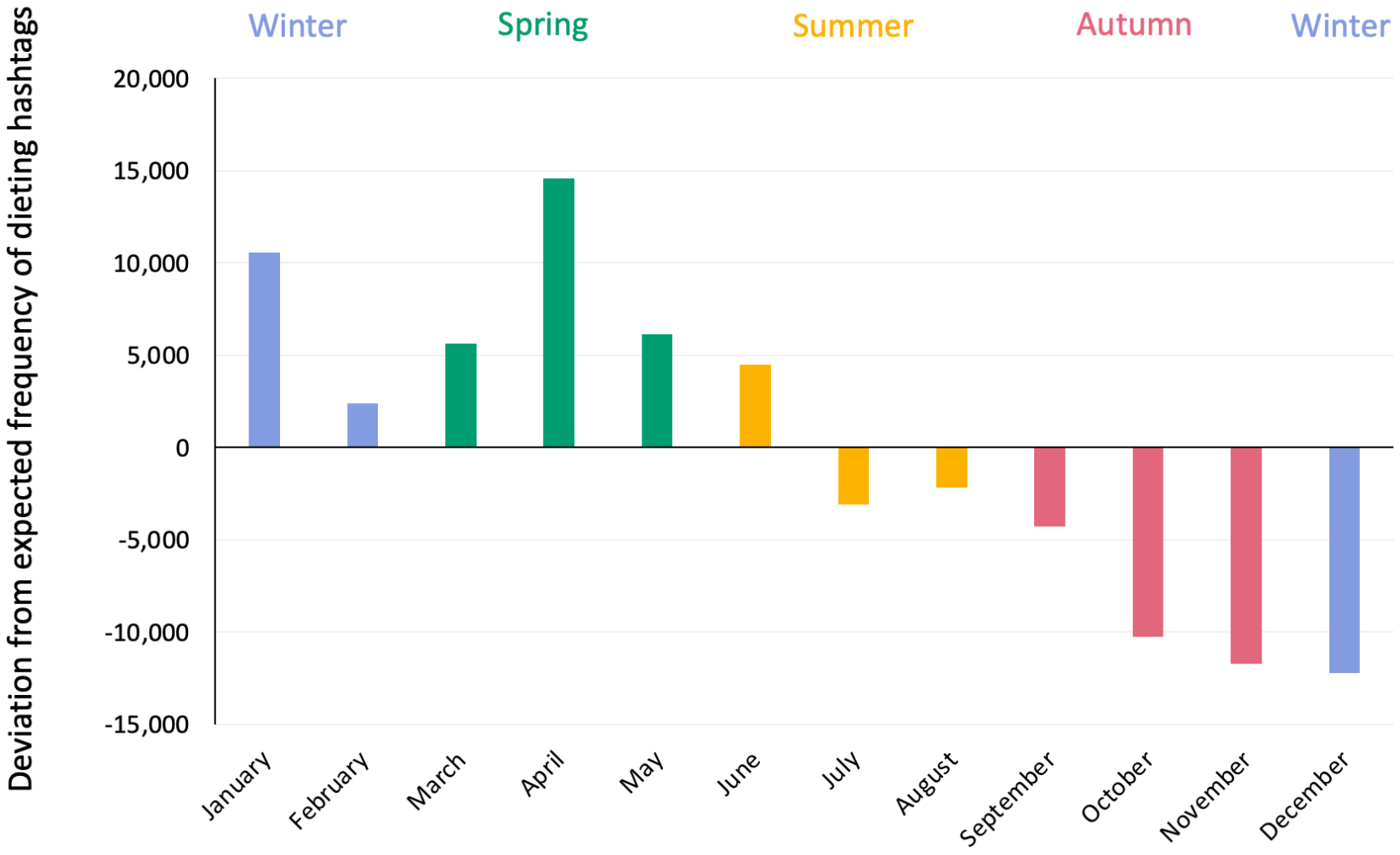

Figure 3. A visualisation of the deviations between the observed frequency of dieting hashtags and the expected frequency of dieting hashtags assuming that seasonal fluctuations do not exist (i.e., when predicting an equal frequency of dieting hashtags per month).

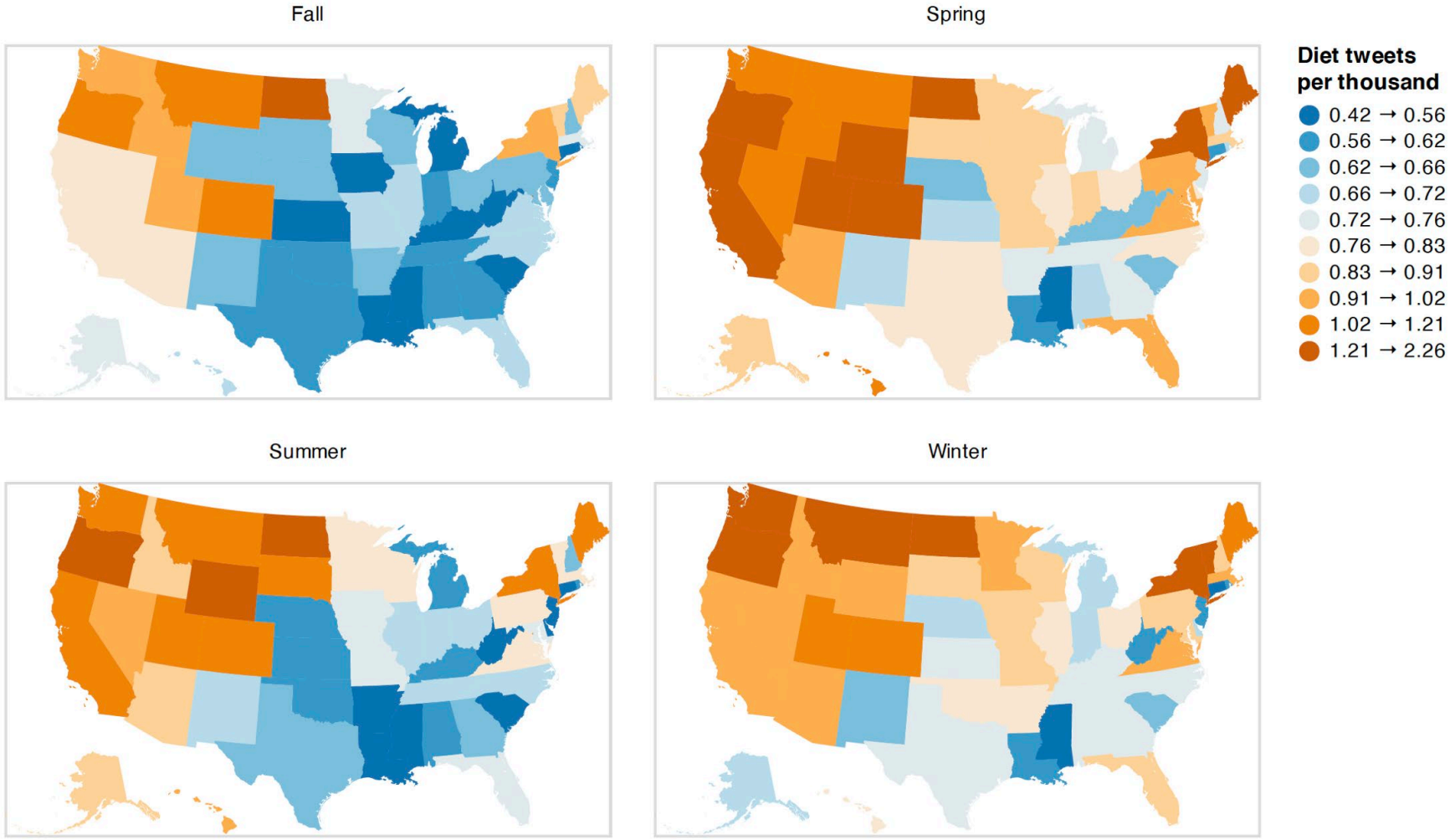

Figure 4. A heatmap showing seasonal differences in the frequencies of dieting tweets in the United States. The four panels correspond to Autumn/Fall (top left), Spring (top right), Summer (bottom left), and Winter (bottom right). As the colour gradient shifts from blue to orange, the frequency of dieting tweets increases. Code to reproduce this heatmap is available on our Open Science Framework page.

Supplementary Table A. Mean positive and negative wordcount in dieting tweets, stratified by season. For comprehensiveness, we have wordcounts for two sets of data: the first for all tweets geolocatable to the United States (used in our chi-square analyses), and the second for all tweets geolocatable to *cities* of the United States (used in our temperature-specific regression analyses). The results are substantively identical: there are no meaningful seasonal differences in the mean number of positive or negative words, or the ratio of positive to negative words, in dieting tweets.

Dieting tweets geolocatable to the United States			
Season	Mean number of positive words	Mean number of negative words	Ratio of positive to negative words
Autumn/Fall	0.71	0.35	2.03
Winter	0.70	0.34	2.06
Spring	0.69	0.33	2.09
Summer	0.73	0.34	2.15
Dieting tweets geolocatable to cities within the United States			
Autumn/Fall	0.70	0.35	2.00
Winter	0.70	0.31	2.26
Spring	0.69	0.33	2.09
Summer	0.74	0.34	2.18