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Infodemiology of Healthy Lifestyle Searches in Indonesia: A Google Trends Analysis, 2004–2024

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ABSTRACT: Google Trends captures relative interest in health information, but conventional analyses of monthly observations may overstate the statistical evidence due to temporal dependence. We reanalyzed 248 monthly observations (January 2004–August 2024) for diet, physical activity, and weight-loss queries in Indonesia. Within-domain composite indices were formed from five, five, and four nonoverlapping search terms, respectively. Differences between the three study-defined periods were estimated using calendar-month-adjusted regression with Newey–West standard errors (12 lags), with Holm adjustment for 9 contrasts. Pearson correlations were examined for series levels and monthly changes. Lag-one autocorrelation ranged from 0.811 to 0.930. Physical activity interest was higher during than before the pandemic-defined period (difference of 29.12 index points; 95% CI 22.87–35.36; Holm-adjusted $p < 0.001$) and lower afterward than during it (−18.27; 95% CI −24.10 to −12.44). The during-versus-pre difference for weight loss (12.71; 95% CI 1.66–23.76) did not remain significant after multiplicity correction ($p = 0.073$). Diet–weight-loss correlation decreased from 0.770 for levels to 0.298 for monthly changes. Online search interest varied across topics and periods; physical activity showed the clearest period difference. Findings are descriptive, sensitive to temporal modeling, and do not establish changes in health behavior or the pandemic's causal effects.

1. INTRODUCTION

A healthy lifestyle includes dietary practices, physical activity, and other behaviors relevant to the prevention of noncommunicable diseases. International and Indonesian guidance emphasizes dietary quality, regular movement, and risk reduction [1-7]. Online searches offer a complementary perspective on public interest in these topics, but search activity does not demonstrate behavior change [1, 8].

Google Trends provides a normalized, time-indexed measure of the relative popularity of specified queries within a selected location and time period [9]. Infodemiology uses such digital traces to examine the distribution and determinants of online health information seeking [10]. Internet use in Indonesia has expanded, and Google Trends has been investigated in nutritional information seeking and infectious-disease surveillance [11-15].

Previous Indonesian research reported fluctuations in diet- and weight-related searches, including around annual holidays and the COVID-19 period [16]. International studies also documented shifts in health-related Google searches during the pandemic [8, 17]. However, comparison of multiple topics over two decades requires attention to how search terms are combined and to

dependence among consecutive monthly observations. In particular, a high correlation between two trending series may reflect shared changes over time rather than synchronous fluctuations in public information needs.

We aimed to describe longitudinal and calendar-month patterns in Indonesian Google search interest in diet, physical activity, and weight loss from January 2004 through August 2024; compare three investigator-defined periods around the COVID-19 pandemic using inference robust to autocorrelation; and evaluate associations across topics both at the level of the original indices and for month-to-month changes.

2. MATERIALS AND METHODS

2.1 Study Design and Data Source

This retrospective ecological infodemiology study reanalyzed archived, publicly accessible Google Trends datasets for Indonesia. No individuals were recruited, no identifiable information was collected, and the analytic unit was the calendar month. The available data comprised 248 consecutive monthly observations from January 2004 through August 2024. Three investigator-defined intervals were used: pre-period (January 2004-February 2020; n=194), during-period (March 2020-June 2023; n=40), and post-period (July 2023-August 2024; n=14). The March 2020 boundary aligns with WHO characterizing COVID-19 as a pandemic on March 11, 2020; the July 2023 boundary follows Indonesia's formal termination of pandemic status on June 21, 2023 [18, 19]. These boundaries provide epidemiological and policy context but are not exposure assignments, and period comparisons cannot identify causal pandemic effects.

2.2 Data Collection and Measurements

The original extraction documentation specified Indonesia as the geographic setting, all search categories, Google Web Search (rather than other Google search products), and a retrieval date of September 1, 2024. Reanalysis used the archived monthly spreadsheet exports and did not issue new Google Trends queries. The archived documentation did not identify the interface-language setting, query batches, or an auditable log of candidate-term screening; these details cannot be reconstructed from the manuscript. The exact query strings retained in the study are reported below. Google Trends relative search volume (RSV) is normalized to a 0-100 scale within the geographic, temporal, and query-comparison context; a value of 100 marks a relative peak, not 100 searches, and zeros may include insufficient-volume observations [20]. RSV is not a count of searches, a measure of the number of search users, or an indicator of actual lifestyle behavior.

Terms were grouped by apparent relevance to diet practices, movement or exercise, and weight reduction. The diet set included five search strings: "diet," "cara diet," "diet sehat," "menu diet," and "makanan diet." Physical activity included five strings: "aktivitas," "gerakan," "manfaat aktivitas fisik," "kebugaran jasmani," and "olahraga." The weight-loss archive contained "menurunkan berat badan," "weight loss," "penurun berat badan," "olahraga menurunkan berat badan," and "diet." The primary weight-loss composite used the first four, excluding the exact duplicate term "diet" to avoid mechanical overlap with the diet composite; all five were included in the existing sensitivity analysis. All expressions other than "weight loss" were in Indonesian. Some strings, particularly "aktivitas" and "gerakan," are broad and may retrieve unrelated contexts; "olahraga menurunkan berat badan" also overlaps conceptually with physical activity. The available records did not document systematic evaluation of alternative synonyms or formal content validation. These are investigator-defined groups of search terms, not built-in Google Trends topics.

For each domain and month, the composite index was calculated as the arithmetic mean of its constituent query-level RSV values (five, five, and four terms for diet, physical activity, and weight loss, respectively). Every component received equal numerical weight after query-specific normalization. Because the archived query series were independently scaled, this procedure did not weight terms by absolute popularity or place them on a shared volume scale. Consequently, the composites capture changes in selected query-index averages within each domain; differences in composite levels between domains must not be interpreted as differences in absolute search volume. No common anchor-query calibration was available in the archived analysis.

Twenty-three entries recorded as "<1" in the physical-activity source file were assigned 0.5 for the main analysis; substituting 0 or 1 was examined in the existing sensitivity analysis. Recorded zeros were retained, but they may represent low-volume suppression rather than an absence of searches. The indices were calculated for each month before aggregation by study period

or calendar month. The index definitions should therefore be understood as pragmatic measures of selected query strings rather than externally validated measures of population interest.

2.3 Statistical Analysis

Descriptive statistics were means and standard deviations (SDs) by study period. To describe temporal dependence in the original index series, lag-one autocorrelations and Ljung-Box tests at 12 lags were calculated. These tests characterize the series but do not replace a full regression-residual diagnostic assessment. Conventional one-way analysis of variance (ANOVA) and Tukey comparisons were recalculated solely for comparison with the former manuscript and were not used for primary inference because observations in adjacent months were serially correlated.

For each search domain, the primary ordinary least squares model regressed the monthly composite index on two binary period indicators (during and post; pre as the reference) and 11 calendar-month indicators (one omitted reference month). In notation, the model was Y(t) = beta(0) + beta(1)During(t) + beta(2)Post(t) + sum gamma(m)Month(m,t) + error(t), with the sum covering 11 nonreference months. Thus beta(1) represents during versus pre, beta(2) represents post versus pre, and beta(2)-beta(1) represents post versus during, each adjusted for calendar month. Month indicators account for recurring differences by month of year without assuming that every annual peak has the same cause. Newey-West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors used a 12-month lag window and a small-sample correction. A 12-lag window was selected to span one annual cycle of monthly observations; it was not chosen by optimization of a data-driven criterion. We report two-sided 95% normal-approximation confidence intervals (CIs) and p values and apply Holm correction to the nine planned period contrasts (three contrasts across three domains). These CIs are not multiplicity-adjusted. Sensitivity to time-trend specification was examined by adding a continuous linear time term, and a joint Wald test evaluated the calendar-month indicators.

Pairwise Pearson correlations were computed for monthly index levels (n=248) and first differences, defined as the current minus preceding monthly index (n=247). Level correlations can reflect shared trends and serial dependence; first differences describe co-movement of monthly changes, but do not guarantee stationarity. Exploratory 95% CIs used paired moving-block bootstrap resampling (12-month blocks; 4,000 replications). For first differences, p values came from standardized linear regressions with Newey-West HAC standard errors (12 lags). A separate Holm adjustment was applied to the three reported, rounded correlation p values, so the adjusted values are approximate. The nominal two-sided significance threshold was $p < 0.05$. Analyses used Python 3.13.5, pandas 2.2.3, NumPy 2.3.5, SciPy 1.17.0, and statsmodels 0.14.6.

3. RESULTS AND DISCUSSION

3.1 Data Characteristics and Longitudinal Patterns

All three primary composite indices contained 248 monthly observations. The pre-, during-, and post-period phases comprised 194, 40, and 14 observations, respectively (Table 1). Lag-one autocorrelation was substantial for diet (0.894), physical activity (0.811), and nonoverlapping weight loss (0.930); all Ljung–Box tests at 12 lags had $p < 0.001$. **Figure 1** displays the indices analyzed in the statistical models, rather than individual search queries. Physical-activity interest increased sharply around 2020 before declining in later years, while diet and weight-loss series showed broader long-term fluctuations.

Table 1. Monthly composite Google Trends indices by investigator-defined study period

Domain	Pre-period, n=194 Mean (SD)	During-period, n=40 Mean (SD)	Post-period, n=14 Mean (SD)
Diet (5 terms)	38.37 (15.87)	33.78 (9.56)	18.10 (4.00)
Physical activity (5 terms)	10.58 (3.96)	39.73 (13.76)	20.80 (5.22)
Weight loss (4 terms)	29.89 (18.55)	42.52 (8.46)	24.59 (4.42)

Values are means of query-specific, separately normalized indices (range 0–100). They are not counts or directly comparable absolute search volumes across domains. Period boundaries: March 2020 and July 2023.

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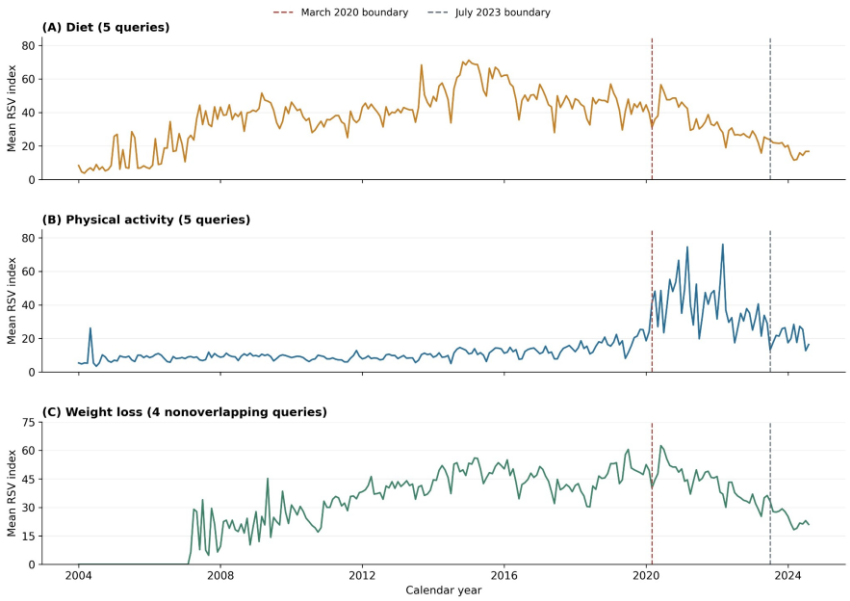


Figure 1. Monthly mean of independently normalized Google Trends search indices in Indonesia (January 2004-August 2024): (A) diet (5 terms), (B) physical activity (5), and (C) weight loss (4 nonoverlapping). Dashed lines indicate March 2020 and July 2023 boundaries. Values reflect relative search interest, not search counts.

Across calendar months, the highest descriptive average occurred in January for diet (39.14; November, 38.98), March for physical activity (21.48), and October for weight loss (33.41); minima were in June, July, and June, respectively (**Figure 2**). Calendar-month indicator tests in the adjusted model were significant for physical activity ($p < 0.001$), but not diet ($p = 0.613$) or weight loss ($p = 0.952$). These profiles do not identify the causes of month-of-year variation or demonstrate recurring peaks in each individual year.

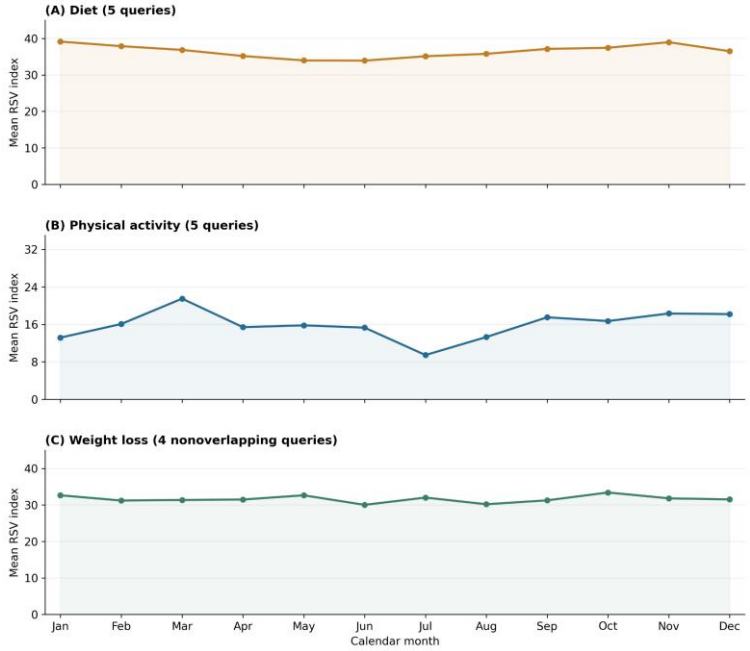


Figure 2. Calendar-month mean search indices for (A) diet, (B) physical activity, and (C) weight loss. Descriptive profiles do not establish recurrent seasonality or event effects. Independently normalized indices are not comparable as absolute search volume across domains.

3.2 Period Comparisons with Autocorrelation-Adjusted Inference

The month-adjusted Newey–West models estimated a marked increase in physical-activity search interest during relative to the pre-period (29.12 index points; 95% CI 22.87–35.36; Holm-adjusted $p < 0.001$), followed by a decline after the during-period (−18.27; 95% CI −24.10 to −12.44; adjusted $p < 0.001$). Post-period physical-activity interest nevertheless remained above pre-period levels (10.85; 95% CI 9.11–12.58; adjusted $p < 0.001$; Table 2).

Diet showed no clear difference during versus before the period (−4.41; 95% CI −15.24 to 6.41; adjusted $p = 0.549$), but post-period values were lower than both pre- and during-period values. For the nonoverlapping weight-loss index, during-versus-pre interest was higher by 12.71 points (95% CI 1.66–23.76; unadjusted $p = 0.024$), but this comparison did not meet the 0.05 threshold after correction for nine tests (adjusted $p = 0.073$). Weight-loss interest declined after relative to during the period (−17.99; 95% CI −26.29 to −9.69; adjusted $p < 0.001$).

Table 2. Adjusted contrasts between study periods in monthly composite search interest

Domain	Contrast	Difference (95% CI) Index points	*p*, HAC	*p*, Holm
Diet	During vs Pre	-4.41 (-15.24 to +6.41)	0.424	0.549
Diet	Post vs Pre	-20.20 (-27.68 to -12.72)	<0.001	<0.001
Diet	Post vs During	-15.79 (-24.80 to -6.78)	<0.001	0.002
Physical activity	During vs Pre	+29.12 (+22.87 to +35.36)	<0.001	<0.001
Physical activity	Post vs Pre	+10.85 (+9.11 to +12.58)	<0.001	<0.001
Physical activity	Post vs During	-18.27 (-24.10 to -12.44)	<0.001	<0.001
Weight loss	During vs Pre	+12.71 (+1.66 to +23.76)	0.024	0.073
Weight loss	Post vs Pre	-5.28 (-14.76 to +4.19)	0.275	0.549
Weight loss	Post vs During	-17.99 (-26.29 to -9.69)	<0.001	<0.001

Differences from OLS models with period and calendar-month indicators; Newey–West HAC standard errors (12 lags), 95% normal-approximation CIs. Holm adjustment was applied across nine contrasts; the 95% CIs were not multiplicity-adjusted and can therefore differ in decision from Holm-adjusted p values. Positive differences indicate higher average search-index values in the first-named period. Analyses are descriptive and not causal.

A sensitivity model additionally accounting for a continuous linear time trend changed the magnitude and, for diet and weight loss, the sign of the during-versus-pre contrasts (diet: −27.35; 95% CI −43.72 to −10.98; weight loss: −20.80; 95% CI −34.36 to −7.24). The corresponding physical-activity contrast remained positive (24.45; 95% CI 17.65–31.24). Thus, period associations for diet and weight loss were not robust to this alternative time-trend specification. Conventional ANOVA estimates were recalculated for comparison with the earlier approach but were not used as the inferential basis here.

3.3 Correlations Between Search Topics

Figure 3 compares Pearson correlations of the composite index levels with those of month-to-month differences. At the level of the original series, diet and weight loss were positively correlated ($r = 0.770$; exploratory 95% block-bootstrap CI 0.549-0.858), as were physical activity and weight loss ($r = 0.357$; CI 0.155-0.513); diet and physical activity showed little level association ($r = 0.012$; CI -0.273 to 0.243). On first-difference series, diet and weight loss had $r = 0.298$ (CI 0.063-0.617; HAC $p = 0.015$), physical activity and weight loss had $r = 0.040$ (CI -0.037 to 0.120; HAC $p = 0.204$), and diet and physical activity

had $r = 0.093$ (CI -0.001 to 0.173; HAC $p = 0.124$). The separate Holm adjustment of the three rounded first-difference p values yielded approximate adjusted p values of 0.045, 0.248, and 0.248, respectively. These exploratory bootstrap CIs were not adjusted for multiplicity; no confirmatory significance claim is made for level correlations.

When the overlapping "diet" query was returned to the weight-loss composite, the level correlation between diet and weight loss increased from 0.770 to 0.820. Replacing the 23 censored physical-activity values with either 0 or 1 had little effect on the correlations. These sensitivities emphasize that observed associations reflect the specification of composite search indices as well as shared temporal variation.

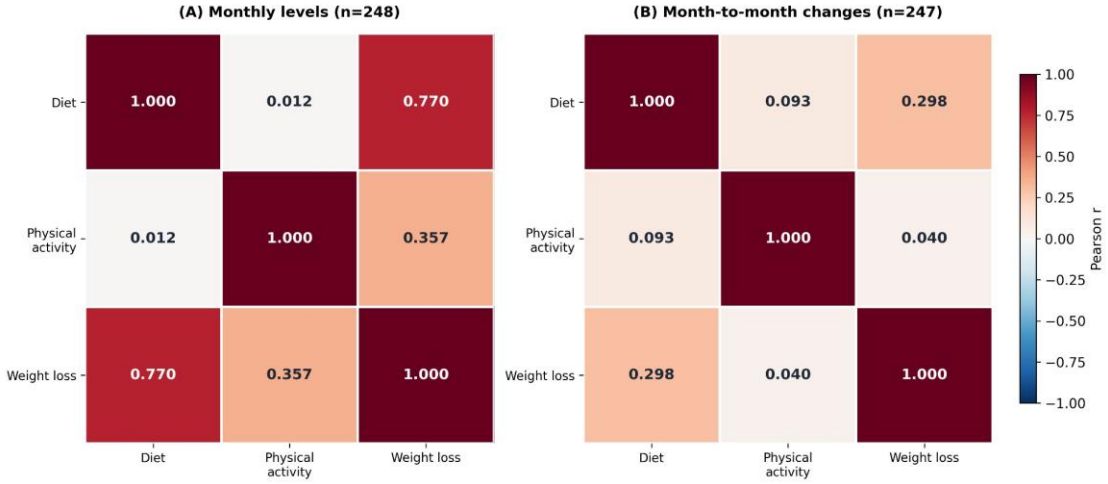


Figure 3. Pearson correlations for (A) index levels (248 months) and (B) first differences (247 months). The weight-loss composite excludes the exact query "diet". Aggregate query correlations do not demonstrate person-level associations or causality.

3.4 Discussion

This reanalysis indicates that online interest in healthy-lifestyle information in Indonesia was not constant during 2004–2024 and that patterns differed across diet, physical activity, and weight loss. Accounting for serial dependence materially changes the certainty of some findings compared with conventional ANOVA. In the primary model, the most consistent result was higher activity-related search interest during the investigator-defined pandemic period and lower interest afterward; its direction was preserved in a sensitivity model with a linear time trend.

Earlier infodemiology studies reported shifts in health-related searching in the COVID-19 era [8, 16, 17]. The chosen periods correspond to identifiable international and Indonesian policy milestones, not randomized or sharply isolated exposures. Home-exercise needs and public-health messages could have contributed to the activity-related pattern, but several competing explanations remain plausible: changing internet penetration and Google use, digital literacy, media coverage, the relative prominence of particular search terms, other contemporaneous events, and shifts in how users seek health information. The three periods also differ substantially in length (194, 40, and 14 months), and no unaffected comparison series was used. Accordingly, observed period contrasts are descriptive associations with calendar intervals rather than estimates of changes caused by COVID-19 [21].

Diet and weight-loss search indices were lower after the study-defined pandemic period than during it. However, the apparent during-versus-pre weight-loss increase was not statistically robust after the nine-test Holm correction, and adding a linear time trend substantially altered estimates for both diet and weight loss. This sensitivity likely reflects the pronounced longer-term fluctuations visible in Figure 1. It would be misleading to report that all topics rose significantly during the pandemic. Similarly, observed peaks by calendar month require cautious interpretation: only physical activity showed evidence of calendar-month differences in the fitted model, and the highest average month is not necessarily a repeatable yearly seasonal phenomenon. These findings cannot be attributed directly to New Year resolutions or the timing of Eid al-Fitr without event-specific analysis [1, 12, 16, 22].

The diet-weight-loss correlation weakened from 0.770 for levels to 0.298 for month-to-month changes; the physical activity-weight-loss correlation similarly declined from 0.357 to 0.040. These changes are consistent with the influence of broad shared temporal patterns on level correlations, but are not proof that level correlations were spurious: differencing changes the target of inference and does not automatically resolve all forms of nonstationarity. Including the same "diet" string in two composites mechanically increased their level correlation, further illustrating dependence on index construction. The modest first-difference diet-weight-loss association retained an approximate Holm-adjusted p value of 0.045 within the three exploratory correlation tests, but this should not be interpreted as a person-level relationship. Aggregate search series cannot show whether the same users searched for both topics, nor do they measure adoption of either behavior [9, 10, 22].

The findings have potential use for monitoring information demand, not as evidence that health communication has altered behavior. Topic-specific search monitoring could inform the timing and content of messages about diet, exercise, and weight management, provided that it is used alongside independent evidence. Future work should triangulate search-index patterns with population surveys, repeated dietary and physical-activity assessments, health surveillance indicators, media or campaign exposure, and information on internet access. Such designs could examine whether increases in search attention correspond to measurable outcomes, rather than treating search interest as a proxy for dietary quality, physical activity, or weight-loss behavior [3, 6, 23].

Several limitations affect measurement validity. Google Trends draws from samples of search activity; repeated downloads, normalization to a particular query and time window, algorithmic or platform changes, and suppression of low-volume searches can influence RSV values. Search terms may be ambiguous, semantically overlapping, or language-dependent. The inclusion of an English phrase among mostly Indonesian strings and the absence of documented alternative-term screening further constrain coverage of relevant information seeking. Independently normalized terms were averaged with equal numerical weight despite unknown differences in absolute popularity; a common scaling anchor was unavailable. Removing the duplicated "diet" query from the weight-loss composite reduced mechanical overlap but did not eliminate conceptual overlap between topics. Substituting 0.5 for values marked "<1" is an imputation, although the previously reported recoding sensitivity had little effect on correlations.

Inference is also limited by marked serial correlation, possible nonstationarity, the relatively short post-period, and dependence of diet and weight-loss period estimates on whether a linear time trend was included. The primary 12-lag Newey-West specification reduces sensitivity of standard errors to certain forms of dependence but does not remove underlying trends or identify causal effects. Alternative HAC lag windows, regression-residual diagnostics, individual-query period models, and common-anchor rescaling would be valuable checks; results for these analyses were not available in the supplied manuscript and are not claimed here. Block-bootstrap CIs, particularly for potentially nonstationary series, should be regarded as exploratory. The dataset excludes individuals who do not use Google, does not identify users' age, sex, socioeconomic position, or location within Indonesia, and cannot link searches to actual eating, exercise, or weight-management practices. Consequently, the reported contrasts and correlations should not be interpreted as clinical or behavioral outcomes.

4. CONCLUSION

Monthly Google searches for diet, physical activity, and weight loss in Indonesia followed different long-term and calendar-month patterns. Activity-related search interest was substantially higher in the study-defined pandemic period than beforehand and decreased afterward, a pattern that persisted under an alternative linear-trend specification. Findings for diet and weight loss were more sensitive to modeling decisions, and correlations weakened after examining monthly changes. The results support cautious use of search interest as a complementary indicator of information demand, not as a measure of lifestyle behavior or evidence of pandemic causation.

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AUTHOR CONTRIBUTIONS

Safrina Oksidriyani: Conceptualization, methodology, project administration, supervision, writing - original draft.

Mardiana: Conceptualization, methodology, validation, supervision, writing - review and editing.

Farida Dwi Rokhmah: Methodology, formal analysis, data curation, visualization, writing - review and editing.

Diah Rahmah Permatasari: Investigation, data curation, resources, project administration.

Bela Prasasti: Investigation, data curation, visualization, writing - review and editing.

Antonius Yudha Kurnia Pratama: Investigation, formal analysis, data curation, visualization.

Addinar Fitri Firdianty: Investigation, data curation, writing - review and editing.

CONFLICT OF INTEREST

We declare that the authors have no competing interests or other interests that might be perceived to influence the results and/or discussion reported in this paper.

ETHICS STATEMENT

The original study documentation reports that ethics committee review and informed consent were not required because only publicly available aggregate Google Trends data were analyzed, with no identifiable participants.

DATA AVAILABILITY STATEMENT

Archived monthly Google Trends exports were used for this study. Data and code access arrangements require confirmation by the corresponding author.

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