Meal Pattern Analysis in Nutritional Science: Recent Methods and Findings

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ABSTRACT

There is a scarcity of dietary intake research focusing on the intake of whole meals rather than on the nutrients and foods of which those meals are composed. This growing area of research has recently begun to utilize advanced statistical techniques to manage the large number of variables and permutations associated with these complex meal patterns. The aim of this narrative review was to evaluate those techniques and the meal patterns they detect. The 10 observational studies identified used techniques such as principal components analysis, clustering, latent class analysis, and decision trees. They examined meal patterns under 3 categories: temporal patterns (relating to the timing and distribution of meals), content patterns (relating to combinations of foods within a meal and combinations of those meals over a day), and context patterns (relating to external elements of the meal, such as location, activities while eating, and the presence or absence of others). The most common temporal meal patterns were the 3 meals/d pattern, the skipped breakfast pattern, and a grazing pattern consisting of smaller but more frequent meals. The 3 meals/d pattern was associated with increased diet quality compared with the other 2 patterns. Studies identified between 7 and 12 content patterns with limited similarities between studies and no clear associations between the patterns and diet quality or health. One study simultaneously examined temporal and context meal patterns, finding limited associations with diet quality. No study simultaneously examined other combinations of meal patterns. Future research that further develops the statistical techniques required for meal pattern analysis is necessary to clarify the relations between meal patterns and diet quality and health. *Adv Nutr* 2021;12:1365–1378.

Keywords: meal patterns, dietary patterns, eating patterns, dietary assessment, principal components analysis, latent class analysis, clustering, decision trees

Introduction

Suboptimal dietary intake is known to contribute to the global burden of chronic noncommunicable diseases, including cardiovascular disease, type 2 diabetes, and certain cancers (1). The accurate assessment of food intake is an essential element of identifying such diet–disease associations and developing advice to support appropriate change in dietary behaviors (2). Traditionally, diet–disease epidemiological studies have focused on linking disease or risk of disease with individual nutrients or foods, with a focus in more recent decades to examining the links with dietary patterns (i.e., the combinations of foods consumed habitually that represent the diet as a whole) (3–7). These approaches reveal valuable insights and have contributed to the development of both nutrient- and food-based dietary guidelines (8). Yet, unlike a meal-based approach, they do not consider foods consumed in combination as part of a meal, the distribution or number of those meals over a day, or the context in which those meals are consumed (9, 10).

A focus on meal-level information in the examination of dietary links to disease risk may improve the provision of meal-based dietary advice and enhance existing food-based dietary guidelines, with practical benefits for individuals relating to meal planning and preparation (10). Furthermore, it has been proposed that a meal-based approach may be more appropriate for personalized nutrition using internet and mobile technology by reducing user burden with regard to data input and supporting meal-based personalized dietary feedback and advice (11).

Research of meal patterns to date has primarily focused on relatively simple statistical approaches based on frequencies—for example, the total number of meals per day (12, 13), the percentage of meals consumed in certain

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Abbreviations used: LCA, latent class analysis; PAM, partitioning around the medoids; PCA, principal components analysis.

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locations with the presence or absence of other people (14, 15), and the percentage of meals that contained certain food groups or combinations of food groups without considering daily patterns (16, 17). However, these approaches cannot simultaneously capture the multiple variables that define meal patterns, such as those relating to the timing, distribution, content, and context of meals (18–20).

More recently, studies have applied advanced statistical data-mining techniques to the concept of meal patterns. These techniques can better capture the complexity that is inherent within dietary intake datasets, while incorporating the many variables that are required for meal pattern analysis (10, 21). Despite the recent growth in their use, no review of these techniques as they apply to meal patterns has yet been published.

The objectives of this review are, first, to provide a brief conceptual and theoretical overview of advanced statistical techniques as they apply to meal pattern analysis and, second, to critically review the research that has used these techniques, examining the meal patterns identified and their associations with diet quality and health, while noting gaps in the literature that warrant further research.

Overview of Statistical Techniques

Meal pattern analysis is the identification of patterns that emerge from measured food-intake variables such as the temporal aspects of meals, their content, and the context in which they are consumed. Individuals are then grouped with those who have similar patterns (10, 17).

The statistical approaches used in meal pattern analysis reduce an interminably vast number of possible patterns—arising from various combinations of foods, times, or contexts related to a given meal—to a smaller number of patterns that are representative of those found in the sample population (22). This smaller number of patterns can be investigated for associations with diet quality or health (18). The statistical approaches used in meal pattern analysis to date include principal components analysis (PCA), clustering, latent class analysis (LCA), and decision trees (9, 18–20, 23–28). This section provides an overview of the underlying principles of these approaches as they relate to meal pattern analysis, as also summarized in **Table 1**. There are a number of statistical techniques that have been used in preliminary steps to the above-mentioned techniques; however, as these preliminary steps were not intended to identify the meal patterns themselves, they are not discussed in this section.

There are considerable differences in the datasets used for the meal pattern analyses discussed in this review and are typically driven by the research question at hand and the feasibility of collecting the required data. The structure of the data used for such analysis can influence the approach taken and is worth considering here before detailing the statistical techniques themselves. Several methods can be used to collect food-intake data—for example, food records, food recalls, and questionnaires. Food records and recalls (e.g., 4-d food diaries or 24-h recalls) collect information about each individual food or ingredient consumed over a specified time period (29, 30). Portion sizes may be determined by estimates based on common household measures or photographs. Alternatively, in the case of food records, foods may be weighed before consumption (29, 30). Each observation in the dataset represents an individual participant and an individual food consumed by that participant with associated information for the quantity of food consumed, its nutrient content, and the time and meal at which it was consumed. There will be multiple observations for each participant representing the multiple foods consumed over the course of the recording period. The nutrient content of these foods can then be summed to give the total nutrient intake per day for each individual or as a mean intake for the sample population. When multiple days of food intake are recorded, the mean daily nutrient intake for individuals or for the sample population can be calculated (29, 30).

On the other hand, questionnaires used in meal pattern analysis do not focus on individual foods consumed by participants, but rather on the meals themselves. The exact approach varies depending on the research question. For example, Englund-Ögge et al. (23) asked participants to report the number of times they consume different meal types (e.g., breakfast, lunch, dinner) per week, Wilson et al. (24) asked participants to report whether they consumed certain meal types (nothing, snack, large meal, small meal) within certain time periods in the previous 24 h, and Riou et al. (28) asked participants to report the number of meals they consume and the time at which they are consumed. While these approaches allow for the investigation of the temporal aspects of meal patterns, they do not allow for the investigation of the content of those meals, which would require data arising from approaches such as food records or recalls.

Principal Components Analysis

PCA is a common statistical technique used to determine variation and uncover patterns in any dataset (22). It is specifically a dimension-reduction method, whereby the number of dimensions in a dataset is equal to the number of variables within the dataset (22). The aim of the analysis is to reduce the number of dimensions by creating indices (i.e., weighted summations) of correlated variables. This reduction allows us to keep the variables that are most important in explaining the variance in the dataset (22) (Table 1).

Let's consider its use in meal pattern analysis. Using PCA to investigate population-based meal patterns, Woolhead et al. (9) examined the percentage energy contribution to overall energy intake from 63 meals (the variables) consumed in a national food-consumption survey conducted in Ireland. These meals were defined by the food groups of which they were composed, thus allowing for the examination of meal patterns based on the content of meals rather than solely the timing or distribution of intakes over a given time period. Each participant had an observed percentage energy value for each of the variables (meals). Hypothetically, the

TABLE 1 Statistical approaches to meal pattern analysis in nutritional science

Statistical approach	Primary objective	Application to meal pattern analysis	References
Principal components analysis	• Variables (dimensions) that are correlated are grouped • The total number of dimensions is reduced by only retaining a selection of grouped variables (components) • The retained components are those that are most important for explaining the variance in the data	• The various possible combinations of foods, meals, timings of intake etc., could lead to millions of possible unique meal patterns • Principal components analysis can reduce this large numbers of combinations to a smaller number of patterns that can be assessed for relations with diet quality or health	Englund-Ögge et al. (23); Wilson et al. (24); Woolhead et al. (9); Murakami, et al. (25)
Clustering	• Observations are grouped in a way that minimizes within-cluster dissimilarity and maximizes between-cluster dissimilarity • Dissimilarity is typically measured using mathematical formulae for distance between points	• Clustering can identify groups of individuals who eat meals at similar times over the course of a day and in a similar context	Chau et al. (18); Khanna et al. (19); Riou et al. (28)
Latent class analysis	• Groups of observations are identified that have similar probabilities of belonging to the same categories in the variables of interest	• Study participants can be grouped based on having high probabilities for eating during the same time periods of the day or consuming the same combinations of meals over a day	Leech et al. (20); Uzhova et al. (26)
Decision trees	• Observations are split into groups based on rules that are applied to the data • Further rules are applied that continue to split the resulting groups until they cannot be further split or reach a stopping rule set by the researcher	• Groups can be split based on the presence or absence of certain food combinations (meals) at various meal types while accounting for some outcome variable of interest • This can allow for the use of meal intake for the prediction of an outcome variable such diet quality or a health biomarker	Hearty and Gibney (27)

percentage energy values for 2 of the meals could be plotted in a 2-dimensional space such as a scatterplot to examine the relations between them. However, to examine the full dataset and assess all possible combinations of just 2 meals would require $\frac{63!}{2!(63-2)!}$ comparisons, resulting in 1953 separate plots. This is clearly not a feasible solution, and each plot would only capture a fraction of the variance in the total data. Woolhead et al. (9) thus used PCA to address this issue by assessing all 63 meals together—that is, examining the datapoints for percentage energy from each of the 63 meals in a 63-dimensional space (22).

PCA identifies components that are linear functions of all variables. In the example above (9), each component is a linear function of the 63 meal variables. However, not all variables will be equally important to all components and this distinguishes the components from each other. The relative importance of a given variable on a particular component is quantified by the variable loading value. A small selection of variables with high absolute loading values are typically selected to characterize each component—for example, 1 component may have high loadings for fruit-based breakfast, sandwich-based light meal, and meat/fish with pasta/rice/potato and vegetables main meal, while another component may have high loadings for cooked breakfast and meat/fish with rice/potato/pasta and soups/sauces main meal (9).

Clustering

Clustering describes several different techniques used to identify subgroups, or clusters, within a given dataset (Table 1). The aim of clustering analysis is to group observations that are least dissimilar among themselves but most dissimilar from observations in other clusters (22). These approaches have been applied to temporal meal patterns (18, 19) and to a combined assessment of temporal and context meal patterns (28). All 3 studies used different methods of clustering. No study has been identified that has applied these techniques to content meal patterns. Clustering methods are not robust in the presence of missing data. While none of the studies reviewed here reported missing values in the variables used for clustering, a variety of methods have been proposed to deal with this issue and are discussed at length elsewhere (31–33).

There are several clustering techniques, some of which have been used in meal pattern analysis and will be discussed here. Hierarchical clustering is an iterative process that starts with each cluster containing just a single observation and ends with only 1 cluster composed of all observations grouped together (22). For example, each observation assessed by Chau et al. (18), who examined meal patterns using this method in 4508 adults in Taiwan, can be represented by a vector containing 6 elements, each corresponding to the energy intake of a single participant during one of six 4-h periods in a day. At each step in hierarchical clustering the 2 of these vectors or groups of these vectors that are least dissimilar from each other are joined until the desired number of clusters are achieved.

The partitioning around the medoids (PAM) clustering method is another iterative process. Unlike hierarchical clustering, the number of clusters sought is prespecified. Initially, observations are randomly assigned to the chosen number of clusters. The medoid of each cluster is then determined; this is the observation in the cluster that is closest to the center of the cluster (34). Observations are then re-assigned to the cluster with the nearest medoid. The medoids for the newly formed clusters are then re-determined and observations re-assigned. This process is repeated until there are no further changes to which cluster each observation belongs (i.e., the variation within clusters is minimized) (34).

Finally, K-means clustering is a similar approach to PAM, with the centroid (based on the mean of the variables in the cluster) being used in place of the medoid to minimize variation within clusters. Both approaches are limited to identifying clusters that can be separated by a straight line.

One of the decisions required when clustering is choosing the number of clusters to represent the data. Different approaches were taken in the studies reviewed here. Chau et al. (18) selected 5 clusters to represent the data as they explained a considerable proportion of the variance (55%), and to choose 6 clusters would only explain a small fraction more (0.5%) of the variance and would render the clusters more difficult to interpret. Riou et al. (28), who used this approach to assess meal patterns in 2994 adults in France, selected 5 clusters based on resampling and a cluster-robustness approach called consensus clustering, which identifies the number of clusters that provide the most stable results across multiple samplings (35). There are numerous other procedures that can be carried out that aim to estimate the optimal number of clusters for a dataset as examined in detail elsewhere (36, 37).

Latent Class Analysis

LCA aims to identify an unobserved, or latent, variable that represents some number of observed categorical variables (38). It assumes that this latent variable is composed of a number of mutually exclusive and exhaustive classes; by this, we mean that each participant can only belong to 1 class and that all participants are assigned to a class. This allows for the identification of subgroups within a sample, based on patterns of multiple observed variables (39). LCA has been applied to both temporal meal patterns (20) and content meal patterns (26). In the context of temporal meal patterns (20) the observed variables applied were binary, denoting the presence or absence of an eating occasion during each hour of the day. This gives 24 time periods with 2 possible observations for each participant, amounting to 2^{24} possible unique patterns of intake. In the case of content meal patterns (26) the data were reduced to the 3 meal types—breakfast, light meal, and main meal—as observed variables, within which each participant was categorized to have consumed 1 of 5, 7, or 5 meals, respectively. This amounts to $5 \times 7 \times 5 = 175$ possible patterns. LCA allows these large numbers of possible patterns to be reduced to a smaller number of latent classes representing the patterns that exist in the sample population (38) (Table 1).

The number of latent classes must be specified before fitting a latent class model to the data. The 2 parameters that must be estimated in order to fit the model to the specified number of classes are the prevalence of each latent class and the probabilities of observing each of the variable categories within each class (38). In the temporal example above, this is the probability of the presence of an eating occasion during each hour of the day (20). For example, of the 3 latent classes reported, 43% of participants belonged to the "conventional" latent class that had a high probability of consuming a meal at midday and 18:00 h. In the content meal pattern example this is the probability of consumption of 1 of the meals at each meal type (26). For example, 1 of the 4 classes reported comprised 9% of the participants who had relatively high probabilities of consuming a cooked breakfast, of skipping a light meal, and consuming a protein- and carbohydrate-based main meal.

Decision Trees

Only 1 of the identified studies applied a supervised statistical approach to meal pattern analysis (27) (Table 1). Supervised approaches aim to use the input variables to predict some outcome variable (40). This is unlike the unsupervised approaches described in the preceding sections where the outcome variable is absent; instead, the aim is to determine associations and patterns among the input variables (40). While different types of decision tree methods are available, Hearty and Gibney (27) applied a C5 decision tree approach using meal intake at either breakfast or main meal to predict whether an individual's diet scored in either the first or fifth quintile of the Healthy Eating Index.

It is possible to use decision trees with both continuous and categorical data, they are generally easy to interpret, and can be represented graphically (41). The decision tree can be represented in a format similar to a hierarchy or tree diagram, where the top of the diagram represents the full dataset, and it is split into specific subsets at each branch (22). In the case of the study by Hearty and Gibney (27), who applied decision trees separately to the breakfast meal type and the main meal type, the top of the diagram represented all participants in the study, each with an associated variable for various food combinations (meals). The values of these variables are either 1 or 0 defining, respectively, whether the given meal was consumed or not at each meal type. Participants were then split into 2 subgroups based on a rule applied to the dataset. The rules applied by Hearty and Gibney (27) were based on the presence or absence of various meals at either breakfast or main meal for each participant. For example, the first rule split the participants by assigning those who consumed the "Bread & Confect/Snack" meal at breakfast to 1 subgroup and those who did not to another subgroup. This process is repeated by applying additional rules to each new subgroup to create further subgroups until no further subgroups can be created. Hearty and Gibney (27) applied a stopping rule which only allowed subgroups to be further split if they contained at least 75 records.

The number of rules applied and the order in which those rules are applied will impact the overall outcome of the final tree. However, given the vast number of combinations involved, it is not computationally possible to compare all trees that could arise from a given dataset. Instead, a "non-backtracking" or "greedy" approach is used; at each split in the tree, the best rule is chosen based on that split alone and not on the potential impact it may have at subsequent splits in the tree (41). Several methods are available for choosing the best rule at each step in the decision tree—for example, statistical significance, information gain, and error reduction (41). The method chosen by Hearty and Gibney (27) was based on information theory; this uses the gain ratio, which expresses the proportion of information that appears to aid prediction that is generated by the different possible rules. The rule with the highest gain ratio at each step is used to split the participants into subgroups (41).

Meal Patterns

Studies are reviewed here under the headings of temporal patterns, content patterns, and combined patterns. There is no section for context patterns as no study was identified that applied advanced statistical techniques to these patterns alone; however, 1 study has investigated the combined patterns of both the temporal and context aspects of meal consumption (28). No other analyses of combinations of different meal pattern types were identified.

Temporal Patterns

Temporal meal patterns refer to those accounting for the distribution of dietary intake over a given time, typically 24 h. In published papers to date, statistical methods used to identify temporal meal patterns have included PCA (23, 24), LCA (20), and clustering (18, 19). The 3 studies using either PCA or LCA all identified 3 patterns, while those using clustering identified 4 to 5 patterns (**Table 2**). Most studies divided the day into time periods of varying durations from 1 h (19, 20) to 4 h (18), or considered periods of different durations throughout the day (i.e., five 3-h periods, one 2-h period, and one 7-h period) (24).

The variables used for pattern identification at the various time periods also differed between studies and were influenced by the method of dietary data collection used. The 24-h recall method was used by 3 studies (18–20) (Table 2). As mentioned above, 24-h recalls produce a detailed food file that lists each individual food or drink consumed within the preceding 24 h as well as a portion (gram amount) for each food and the associated nutrients for each food. Each of these foods are reported within a specific meal/time context (e.g., breakfast, lunch, dinner, snack), which allows derivation of nutrient and energy intake at each meal; these data can then be used as input variables for meal pattern analysis. Using data from 24-h recalls, Chau et al. (18) used the energy content of each meal, while Khanna et al. (19) used the energy content of each meal relative to total energy intake (% contribution to total energy). A binary variable was used by Leech et al. (20) denoting whether or not an eating event had occurred during each hour of the day; only eating events with $\geq$210 kJ were considered. The 2 studies using energy intake as an indicator can allow comparisons between groups in relation to the quantity (in terms of energy) consumed during the various time periods of the day (18, 19). This is not captured, however, when there is only an indicator as to whether or not an eating event occurred during the various time periods (20). The use of percentage contribution to total energy accounts for the fact that, while individuals may differ in their total energy intake, they may have similar temporal patterns in relation to how that energy is distributed throughout the day (19).

The remaining 2 studies used questionnaire-based methods of dietary data collection, which did not allow for the derivation of nutrient or energy intake at each meal because information regarding individual foods and portion sizes was not gathered using these methods. Englund-Ögge et al. (23) used the data associated with 8 different meal types (breakfast, morning snack, lunch, afternoon snack, dinner, evening snack, supper, night meal), where participants reported the frequency at which they consumed each meal, within the week, from 0 to 7 times/wk. Finally, Wilson et al. (24) asked participants to report, for each time period, whether they ate nothing, a snack, a small meal, or a large meal and whether the drank nothing, alcohol, water, or something else. Points were assigned to the responses as follows: 1 point for a snack, 3 for a small meal, and 5 for a large meal; water was assigned no points, with other beverages assigned 1 point. The number of points during each time period was calculated relative to the total number of points in the day (24).

Although differing approaches to meal pattern analysis were applied across the studies, there were a number of similarities identified. One pattern that was similar across all studies was that which consisted of 3 meals/d with few or no snacks. The 3 meals typically occurred at times that are culturally associated with breakfast, lunch, and dinner (18, 19, 23, 24). A similar pattern was found by Leech et al. (20) with respect to lunch and dinner meals but without reference to breakfast. This 3 meal/d type of pattern is associated with higher intakes of protein, PUFAs, calcium, phosphorus, vitamin D, and vitamin E and lower carbohydrate intake (adjusted for age, sex, educational level, employment status, chronic disease, geography, and day of dietary recall) (18) and better overall diet quality

TABLE 2 Summarized findings of studies using advanced statistical approaches for meal pattern analysis[1]

Study (reference)	Country	Population	Statistical approach	Data-collection method	Meal pattern construct	Meal patterns	Selected diet quality findings	Selected health findings
Chau et al. (18)	Taiwan	Adults, $n = 4508$	Clustering	24-h recall	Temporal	5 patterns based on dietary intake during six 4-h time periods	Traditional timing pattern (3 meals/d) had the highest nutrient density; delayed lunch with little or no morning intake pattern had the lowest nutrient density	N/A
Englund-Ögge et al. (23)	Norway	Pregnant women, $n = 65{,}487$	PCA	Meal-frequency questionnaire	Temporal	3 patterns based on weekly frequency of 8 meal types (e.g., breakfast, morning snack, lunch, etc.)	N/A	The lowest risk of preterm delivery relative to the first quartile was seen among those in the third (HR: 0.89; 95% CI: 0.79, 0.99) and fourth (HR: 0.88; 95% CI: 0.78, 0.99) quartiles for main meal pattern (3 meals/d) with $P = 0.046$.
Wilson et al. (24)	Australia	Adults, $n = 1304$	PCA	Food habits questionnaire	Temporal	3 patterns based on dietary intake during 7 time periods	N/A	No relation between meal patterns and mood disorders at baseline; after 5 y there was a higher prevalence of mood disorders in those with increased (PR: 1.85; 95% CI: 1.11, 3.09) or consistently high (PR: 2.04; 95% CI: 1.20, 3.28) adherence to the late pattern (lower intakes in morning and higher at night) relative to those with low adherence, with $P < 0.001$
Leech et al. (20)	Australia	Adults, $n = 5242$	LCA	24-h recall	Temporal	3 patterns based on dietary intakes in each hour of the day	N/A	N/A
Leech et al. (42)	Australia	Adults, $n = 4544$	As described by Leech et al. (20) above				Grazing pattern (frequent eating starting and continuing later in the day) had the lowest diet quality score on the Dietary Guidelines Index	No association between patterns and BMI, BMI category, or waist circumference in the model adjusting for the highest number of covariates

(*Continued*)

TABLE 2 (*Continued*)

Study (reference)	Country	Population	Statistical approach	Data-collection method	Meal pattern construct	Meal patterns	Selected diet quality findings	Selected health findings
Leech et al. (43)	Australia	Adults, $n = 4482$	As described by Leech et al. (20) above				N/A	Among women, the later lunch pattern (later lunch and evening meal than conventional times) compared with the conventional pattern (3 meals/d at conventional times) was positively associated with systolic and diastolic blood pressure and hypertension prevalence in the model adjusting for the highest number of covariates
Khanna et al. (19)	United States	Adults, $n = 7565$	Clustering	24-h recall	Temporal	4 patterns based on dietary intake at each hour of the day	N/A	N/A
Eicher-Miller et al. (44)	United States	Adults, $n = 9326$	As described by Khanna et al. (19) above				Cluster 1 (evenly spaced 3 meals/d with similar energy content) scored the highest Healthy Eating Index score; cluster 4 (5 meals/d, frequent intake at midday and midnight) scored the lowest	Greater proportion of those in cluster 1 had normal BMI and lower proportion of those in cluster 1 had overweight/obese BMI than those in other clusters
Woolhead et al. (9)	Ireland	Adults, $n = 1500$	PCA	Food diary	Content	12 patterns based on combinations of foods consumed at each meal	N/A	N/A
Murakami et al. (25)	Japan	Adults, $n = 242$	PCA	Food diary	Content	11 patterns based on combinations of foods consumed at each meal	N/A	N/A
Uzhova et al. (26)	Ireland	Adults, $n = 1500$	LCA	Food diary	Content	4 weekday and 3 weekend patterns based on combinations of foods consumed at each meal	Differences between different patterns in nutrient intake were reported, but no clear differences in overall diet quality	Those consuming the meal pattern "cooked breakfast, skipped light meal, and protein-carbohydrate main meal" had higher diastolic blood pressure ($P < 0.05$)

(*Continued*)

TABLE 2 (*Continued*)

Study (reference)	Country	Population	Statistical approach	Data-collection method	Meal pattern construct	Meal patterns	Selected diet quality findings	Selected health findings
								compared with "cereal and/or toast at breakfast, sandwich for light meal, and protein-carbohydrate or just protein main meal," and higher serum ferritin compared with "cereal and/or toast for breakfast, skipped light meal, and protein-carbohydrate main meal" (OR: 3.14; 95% CI: 1.63, 6.03)
Hearty and Gibney (27)	Ireland and United Kingdom	Adults, $n = 1379$	Decision tree	Food diary	Content	Daily patterns not given; 10 food combinations identified that were likely to predict whether an individual was in the first or fifth quintile for the Healthy Eating Index	Meals likely to predict a lower Healthy Eating Index score were "bread and confectionary/snack," "breakfast cereal," "meat/fish products and chips," "pizza," and "chips and fruit/veg/salad"; those more likely to predict a higher score were combinations of breakfast cereal, fruit juice, and bread, "rice/pasta dish and fruit/veg/salad," "potatoes, veg/meat and yogurt," "fruit/veg/salad," and "potatoes and veg/fish"	N/A
Riou et al. (28)	France	Adults, $n = 2994$	Clustering	Questionnaire	Temporal and context	5 patterns based on number and location of meals, and activities and others present during meals	Those following the type 3 pattern (3 meals/d eaten at home with family) were most likely to consume fruit and vegetables daily	N/A

[1]LCA, latent class analysis; N/A, not applicable; PCA, principal components analysis; PR, prevalence ratio.

(adjusted for sex, ethnicity, age group, BMI, survey year, and household poverty-income ratio) (44) compared with other identified patterns. Eicher-Miller et al. (44) also found that a greater proportion of those following this pattern had normal BMIs and a lower proportion had raised BMIs compared with other patterns. When applied to intakes up to 22 wk of gestation of a group of pregnant women in Norway (n = 65,487), those in the highest 2 quartiles for adherence to this type of pattern were found to have a lower risk of preterm delivery compared with those in the lowest quartile for adherence to that pattern. This analysis adjusted for maternal age, prepregnancy BMI, height, parity, total energy intake, maternal education, marital status, smoking status, income, previous preterm delivery, fiber intake (as an indicator of overall healthy eating), alcohol intake, first trimester nausea, irregular work hours, and physical activity level. No associations with preterm delivery were identified within other meal patterns (23) (Table 2).

Some of the other patterns identified in these studies could be considered variations of this pattern. These typically also included 3 meals/d but with self-reported consumption of "snack meals" rather than "main meals" at these times (23), with 1 to 2 additional intakes in the afternoon and/or night (18), or with timing of lunch intake later in the day than considered traditional. The later lunch pattern has been positively associated with systolic blood pressure and diastolic blood pressure among women compared with those following the more traditional timing of this pattern. The association remained after adjustment for educational level, country of birth, smoking status, physical activity, sleeping habits, overall diet quality, and BMI (43) (Table 2).

Another common pattern identified was that with little or no intake in the morning, typically known as breakfast skipping. Within those following such a pattern, peaks in intake typically happen later in the day, from noon onwards (18, 23, 24). Wilson et al. (24) (adjusting for sex, age, marital status, social support, education, work schedule, BMI, and smoking) examined the impact of meal patterns on mood in 1304 adults in Australia and found a higher prevalence of mood disorders (i.e., the lifetime prevalence of depressive symptoms) after 5 y in those whose adherence to this pattern had either increased or been consistently high compared with those with low adherence. No significant associations with mood disorders were identified among the other patterns either at baseline or at follow up (Table 2).

The final pattern that was common among multiple studies related to a pattern characterized by many smaller intakes spread over the day rather than a low number of larger distinct intakes. This was typically referred to as a grazing pattern (19, 24) and has been associated with the lowest diet quality compared with other patterns (44). In the case of the study by Leech et al. (20) this pattern was the same as the pattern having little or no intake in the morning and was found to be associated with the lowest diet quality compared with other patterns (42). No associations were found, however, between that pattern and adiposity, adjusting for educational level, country of birth, smoking, physical activity, and sleep duration (42) (Table 2).

Khanna et al. (19) additionally identified 2 other patterns that were more likely to have the largest intake in late afternoon and early evening and the second largest in the morning and afternoon, or vice versa. No differences were identified with regard to diet quality between these patterns (44) (Table 2).

Content Patterns

Content patterns require a different approach from those outlined in the previous section on temporal patterns (10). As the aim of analyzing content meal pattern analysis is to summarize the content of meals (in terms of food groups), it is not sufficient to only examine the variables used for temporal meal patterns. For example, only assessing the energy content of meal types or the energy consumed during various time periods of a day provides information about how intake is distributed between the meals or throughout the day but not about the types of foods that provided that energy (9). The approaches taken, therefore, in the collection of data for the assessment of content meal patterns must gather the information describing actual food intakes. In addition, the statistical approaches used must be able to reduce a huge number of possible food combinations that make up meals into a smaller number of interpretable groups.

Of the 4 studies identified that assessed content patterns, dietary intake data were collected using 4-d (9, 26), 7-d (27), and 4 × 4-d (25) food diaries (Table 2). As discussed above, similar to the data collected by 24-h recall, these data are stored in a comprehensive food file, detailing each individual food consumed by each participant with the location, day, the time at which those foods were consumed, and whether they formed part of a meal in combination with other foods. The mass in grams of each consumed food is also recorded, allowing for the determination of the energy or nutrients consumed from a given food, meal, or during a given time period.

To reduce the huge number of possible combinations of unique foods eaten by a study population and allow for meaningful pattern analysis, all 4 studies first condensed the unique foods consumed into more aggregated food groups, resulting in 20 (9, 25, 26) and 62 (27) food groups in these studies, which were developed based on nutrient profile and culinary use of specific foods. Three of the studies then applied the frequent-item-sets data-mining method to categorize the most commonly consumed food-group combinations at each different meal type identifying 63 (9) and 80 (25) food-group combinations at breakfasts, light meals, main meals, snacks, and beverages. Uzhova et al. (26) further aggregated these categories to 14 generic meals (breakfast, light meals, and main meals only). Hearty and Gibney (27) categorized generic meals based on the main food groups in each meal, identifying 134 food group combinations, but do not appear to have used the frequent-item-sets method. The nutrient composition of these commonly consumed meals was then determined, and they were denoted as generic meals (27). Variables from these generic meals were then used as the input to the statistical techniques (decision trees, PCA, and LCA) that identified meal patterns.

There are other methods that could conceivably be used to derive generic meals in place of the frequent-item-sets method, including topic modeling, Gaussian copula graphical models, and PCA (45–47). Like previous methods, the application of these methods also required foods first to be condensed into food groups. White et al. (45) applied topic modeling to 60 food groups to identify generic meals. Each generic meal was based on the probability of each food group appearing within a given meal. Labels were assigned by the authors to the meals to describe the meal type in question (e.g., breakfast, lunch, etc.) based on the top 10 most probable food groups in a given generic meal. Fifteen generic meals were identified. Another approach used 39 food groups with semiparametric Gaussian copula graphical models to identify food groups that are correlated, and therefore likely to be eaten together as part of a meal (46). Finally, Murakami et al. (47) used PCA to identify meal-specific dietary patterns, which could possibly be used to generate generic meals. Individual foods were condensed into 22 food groups, and PCA was carried out based on the amount of each food group consumed at each meal type (breakfast, lunch, or dinner). While these studies applied statistical techniques to identify generic meals in their sample populations—a preliminary step in the analysis of content meal patterns—they did not go on to use these generic meals to assess meal patterns themselves (i.e., either how combinations of these generic meals are consumed over time or how they are related to health or diet quality).

Hearty and Gibney (27) applied artificial neural networks and decision trees to determine if the generic meals identified could predict whether participants belonged to the first or fifth quintile for Healthy Eating Index score; however, only the findings from the decision tree approach were described at a meal level (Table 2). For example, generic main meals such as "meat/fish and chips," "pizza," or "chips and fruit/veg/salad" were reported as predictive of quintile 1, whereas generic main meals such as "rice/pasta and fruit/veg/salad," "potatoes, veg/meat and yogurt," "fruit/veg/salad," or "potatoes and veg/fish" were reported as predictive of quintile 5. Different combinations of these meals over time, however, were not reported (27).

Of the 3 studies that did examine different combinations of meals within a given time (e.g., day), 2 were carried out in the same Irish cohort using PCA (9) and LCA (26), while 1 study was carried out in a Japanese cohort using PCA (47). The food groups used to define generic meals differed between the 2 studies that used PCA. The approach taken by Uzhova et al. (26) differed not only in their use of LCA but also through the use of an additional aggregation step in defining generic meals, excluding the analysis of snacks and beverages, accounting for skipped meals, and distinguishing between weekday and weekend meal patterns.

Seven of the 11 meal patterns identified in the Japanese cohort were likely to include vegetables and/or rice as part of a breakfast meal (47), whereas none of the 12 (9) or 7 (26) meal patterns identified in the Irish cohort contained breakfasts that were likely to consist of either vegetables or the rice/pasta/potatoes food group. All 3 studies identified patterns that included bread-based breakfasts and other patterns where vegetable consumption was unlikely. Although Uzhova et al. (26) did not include beverages in their analysis, both Murakami et al. (47) and Woolhead et al. (9) identified meal patterns that were likely to include consumption of alcoholic beverages.

The meal patterns characterized by bread-based breakfasts with rice, vegetables, and meat/fish at both light meal and main meal identified by Murakami et al. (47) had comparable patterns identified by Woolhead et al. (9) and Uzhova et al. (26) but with a sandwich-based light meal in place of rice, vegetables, and meat/fish. Further similarities can be identified between the 2 studies in the same Irish cohort with common patterns, including those based on cereal/toast breakfast, sandwich light meal, and protein-carbohydrate–based main meal and others based on a higher likelihood of fruit consumption at breakfast, a light meal that does not contain bread, and likely to have lower overall meat intake. Uniquely, Woolhead et al. (9) identified a pattern characterized by consumption of confectionary at multiple meals. While consumption of confectionary was a feature in some of the patterns identified by Murakami et al. (47), it was not the defining feature in any of the patterns. As the confectionary food group was further aggregated into other generic meals in the approach taken by Uzhova et al. (26) it is not likely that such a pattern could have been identified in that study.

Uzhova et al. (26) were the only authors to distinguish between weekday and weekend meal patterns and to investigate the relations between patterns and clinical variables. Four dominant weekday patterns and 3 dominant weekend patterns were identified by Uzhova et al. (26). One meal pattern was found to be common to both weekdays and weekends, which consisted of cooked breakfast, skipped light meal, and protein-carbohydrate–based main meal. However, those who consumed this pattern at the weekend tended to consume greater quantities of potatoes/potato dishes and have a greater overall energy intake than those who consumed the pattern primarily on weekdays. While those consuming certain meal patterns were found to have higher or lower intakes of certain nutrients, no general conclusions could be drawn regarding relations between certain meal patterns and overall diet quality. Clinical variables were assessed after participants were grouped based on their dominant meal patterns for both weekends and weekdays. Significant differences were identified between those with the same weekday pattern (cereal and/or toast breakfast, skipped light meal or sandwich, and protein-carbohydrate–based main meal) but differing weekend patterns. Those with a combination of the above weekday pattern and a weekend pattern consisting of cooked breakfast, skipped light meal, and protein-carbohydrate main meal were more likely to have a higher diastolic blood pressure compared with those with a weekend pattern consisting of cereal and/or toast breakfast, sandwich light meal, and protein-carbohydrate or just protein main meal, and a higher serum ferritin compared with those with a weekend pattern consisting of cereal and/or toast for breakfast, skipped light meal, and protein-carbohydrate main meal. Despite this, there was no clear relation between the meal patterns and multiple clinical variables. Those consuming different meal patterns were not found to be different with regard to anthropometry, blood lipids, glucose, or C-reactive protein (CRP) (26). The analyses carried out by Uzhova et al. (26) adjusted for age, sex, social class, and energy intake.

Combined Patterns

One study was identified that investigated different types of meal patterns in a single population. Riou et al. (28) investigated combinations of both temporal and context patterns in 2994 adults in France. Dietary intake data were collected by a questionnaire regarding the number of meals consumed and the time at which those meals were consumed. To assess temporal patterns, days were split into 6 time periods ranging from 2 to 5 h in duration and participants were categorized as having consumed a meal or not during these periods, with the number of meals consumed also being counted. Context patterns in this study related to observations external to the meals. Specifically, the contextual variables examined by Riou et al. (28) included location (home, workplace, restaurant), with whom the meal was consumed (alone, family members, colleagues, or friends), and activities during the meal (television, radio, computer, reading, chatting). Patterns were identified based on these variables using the partitioning around the medoids clustering method (Table 2).

Five meal patterns were identified. The temporal aspects of these meal patterns hold similarities with the patterns described in the temporal patterns section above. Three of the patterns identified were likely to have 3 meals/d at times culturally associated with breakfast, lunch, and dinner. These patterns differed in their contextual aspects. One of the patterns represented those likely to have meals at work or a restaurant with colleagues or friends while chatting; another represented those likely to have meals at home, mostly alone, and therefore unlikely to chat but likely to watch television or listen to the radio during meals; the third of the 3 meals/d patterns was characterized by eating at home with family while chatting (28).

Two of the patterns identified were composed of those likely to consume 1 to 2 meals/d and not consume breakfast. One of these patterns was primarily characterized by consumption of meals at home with family while watching television, while the other pattern represented those who were likely to consume meals at work or in a restaurant with friends or colleagues while chatting (28).

The authors considered differences in food-group intake across the identified patterns, adjusting for gender, age, education, occupation, income, underprivileged neighborhoods, household type, and loneliness. When compared with the group characterized by consumption of 3 meals/d at home with family while chatting, all other patterns had poor adherence to the 5-a-day consumption guideline of fruit and vegetables; this was particularly pronounced in those following the 2 patterns that typically did not consume breakfast, who were also less likely to adhere to the 3 dairy products/d guideline (28).

Discussion

Meal-based methods of dietary assessment are a departure from the more familiar epidemiological methods that require detailed and accurate reporting of individual food intakes (11). While meal-based methods may not offer the same degree of detail and accuracy, they can complement existing food-based dietary guidelines and may be superior for use in personalized nutrition delivered via internet and mobile technology due to the potential for reduced burden of data collection (11). The use of advanced statistical techniques that inform these meal-based methods is still an emerging area, with only 10 published studies identified (9, 18–20, 23–28).

Despite the methodological differences among studies, some common patterns prevailed in the temporal patterns of meal consumption: the 3 meals/d, skipped breakfast, and grazing patterns (18–20, 23, 24). The patterns relating to the content of meals, however, were more heterogenous than the temporal patterns, with fewer consistent findings between studies. This may reflect differences arising from studies of populations with known differences in the types of foods consumed; that is, foods consumed as part of a typical Japanese diet differ from those consumed as part of a typical Western diet (48). These differences were also observed in this review comparing the meal patterns among these 2 study populations. For example, breakfasts consumed by a Japanese cohort were likely to include rice and/or vegetables (25), whereas none of the breakfasts identified in an Irish cohort contained these food groups (9, 26).

Another source of differences between content meal patterns is the varying ways in which foods are grouped (9, 25–27). In this regard, the study of content meal patterns shares similarities in approach with the study of dietary patterns insofar as both condense the unique foods consumed by the study population into a prespecified number of food groups (4). All studies reviewed here used pre-existing food groups from previous research; no attempt has yet been made to create groups specifically for use in meal pattern analysis. It has been suggested by Newby and Tucker (49) that, in general, all studies need not use the same food groups, but instead, the choice of groupings should be driven by the research question at hand. However, it is important to note that, as the use of food groups introduces a degree of subjectivity and prior knowledge into what are otherwise data-driven approaches, the choice of groupings will likely impact patterns identified (4, 49). This, in turn, has likely given rise to some of the differences observed in this review between the content meal patterns from studies using different food groupings and highlights the need for careful consideration of the food groups used.

Given the range of statistical approaches (PCA, clustering, LCA, decision trees) applied to meal pattern analysis, comparisons between studies should be interpreted with caution. The extent to which the use of different approaches impact the outcome is unclear as, to the authors' knowledge, no studies have compared the use of different statistical techniques to identify meal patterns in the same study population. Future research comparing approaches to meal pattern analysis could provide important methodological insights, such as those reported for the more frequently researched area of dietary patterns that also uses techniques such as PCA and clustering (50–55).

Much of the research carried out in meal pattern analysis has been exploratory in nature, identifying patterns of meal consumption that exist in the sample population (9, 18–20, 23–25, 28). While exploratory research forms an essential part of the scientific process, it is not without limitations (56, 57). Results from these data-driven approaches may not be generalizable to samples from other populations (9). While common dietary patterns have been identified in different populations (49), this has yet to be confirmed for meal patterns. Exploratory analyses identify groups within the sample population. Groups identified by these methods are typically assigned descriptive names by the researchers. These names introduce some subjectivity and should be interpreted with caution as there is no way of quantifying the variability within each group with regard to how well each member of the group is represented by the name assigned (40). It is not possible to determine the likelihood that these groups truly exist in the whole population rather than merely existing in the sample data (40). However, it may be possible to determine whether the patterns are biologically meaningful if there are associations with health/disease status (49).

The meal pattern research reviewed here has primarily used unsupervised statistical techniques to identify groups of individuals with similar meal patterns. The research examining relations between these meal patterns and diet quality or health outcomes remains sparse and warrants further investigation. Only 6 studies have examined these relations with regard to temporal patterns (18, 23, 24, 42–44), 1 study with regard to content patterns (26), and 1 study with regard to combined temporal and context patterns (28). In brief, those following the more traditional 3 meals/d pattern tended to have a higher diet quality than those following a skipped breakfast or grazing pattern (18, 23, 24, 42–44). Unlike temporal meal patterns, no individual content meal patterns have been identified as having notably stronger relationships than other patterns with either diet quality or health outcomes (26). The single study of combined temporal and context patterns by Riou et al. (28) identified those following a pattern characterized by 3 meals/d consumed with family while chatting as having greater adherence to the 5-a-day guideline for fruit and vegetable consumption.

Given their observational nature, the results from these studies may be impacted by confounding. Different variables were chosen in different studies as covariates to adjust for confounding. These choices can also impact results and should be justified based on existing evidence or theoretical knowledge of their impact on confounding (58). While the covariates used were listed in all the studies reviewed here (18, 23, 24, 26, 28, 42–44), not all provided a clear justification for their choice (26, 28, 44). The decision tree approach taken by Hearty and Gibney (27) did not account for covariates. Future work in this area should consider approaches to account for covariates—for example, the use of adjusted residuals from a regression model as the input for the decision tree (59). It should also be noted that these observational studies do not establish a cause-and-effect relation but may provide data for causal inference and potentially inform future intervention studies (60).

This review examined studies in 3 main categories of meal patterns—namely temporal, content, and context patterns. These classifications were initially put forward by Mäkelä et al. (17) in the context of social and cultural aspects of meals using the terms eating patterns, meal format, and social organization of eating. They were further adapted to the nutrition context by Leech et al. (10), who used the terms patterning, format, and context.

While no consensus yet exists regarding the terminology, the current 3-category approach accounts for the fact that people do not perceive dietary intake purely as a collection of nutrients, foods, or indeed meals (61) by capturing information regarding timing, social, and behavioral aspects of eating occasions (10). Despite this, other aspects of meal patterns have not yet been examined using the statistical approaches reviewed here. For example, no studies were identified that examined sensory, psychological, or physical aspects, such as emotions, satisfaction, appetite, fatigue, etc., alongside those other aspects of meal patterns mentioned above. Furthermore, only limited aspects of temporal meal patterns have yet been examined. The research to date has primarily focused on the variation in meal intakes across a 24-h period. Only 3 studies examined the variation between weekdays and weekends with the same temporal patterns being identified on both weekdays and weekends (18, 24). With regard to content meal patterns, however, participants were found to adhere to different patterns on weekdays compared with the weekend (26). No seasonal differences were identified in temporal meal patterns by Chau et al. (18), but this has not been examined with regard to content or context meal patterns. Only 1 study was identified that traced meal patterns across a number of years; Wilson et al. (24) found that the same temporal patterns existed after 5 y in a cohort of Australian adults and that participants were likely to fall into the same meal pattern category at follow-up.

Expanding meal patterns to include these aspects would increase the complexity and require a multidisciplinary approach (62); however, this may give rise to further useful insights about meal patterns. Furthermore, mobile technology allows for the inclusion of such additional variables through ecological momentary assessment—that is, the assessment of people's experiences of their environment in real time (21, 63). Further development of the statistical approaches to meal pattern analysis will allow for the investigation of combinations of these variables and how they change over time (21). In particular, supervised statistical approaches have the capacity to identify associations between meal patterns and overall diet quality or health in individuals for whom these data have been collected, and then used to predict diet quality or health outcomes for other individuals (without diet quality or health data) based on their meal patterns (27). This, in turn, may have applications in personalized nutrition using internet and mobile technology (11).

Conclusions

A range of statistical techniques provide feasible solutions to interpreting complex dietary intake data and detecting insightful patterns of meal consumption related to the timing, content, and context of meals. The observational studies reviewed here suggest that meal patterns consisting of 3 meals/d are associated with increased diet quality compared with the skipped breakfast or grazing meal patterns; however, further research is required to validate these findings. No clear associations with diet quality or health have been identified for meal patterns defined by the content of those meals or context in which they are consumed. To greater elucidate the role of meal patterns in diet quality and health, future research should aim to further develop the statistical approaches that are applied. Research is lacking on the simultaneous analysis of multiple meal pattern categories, how meal patterns vary over time, and the extent to which the grouping of foods and different types of statistical techniques impact overall outcome. These advances will be important if meal pattern research is to be applied to internet- and mobile-based dietary assessment and feedback.

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