The Lifecycle of a Digital Food Trend: A Literature Review

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1 Introduction

In the modern world, food trends emerge and spread with unprecedented speed, driven largely by the decentralized power of social media and online communities (Cash et al., 2022). Platforms such as TikTok, Instagram, Reddit, and YouTube have changed the way recipes, ingredients, and diets capture attention and gain momentum across global audiences (Cash et al., 2022; Drescher et al., 2023). Viral recipes such as baked feta pasta that garnered more than 550 million views or the rise of niche health trends such as #Veganuary demonstrate how quickly user-generated content can influence the behavior and dietary habits of millions, particularly younger demographics (Drescher et al., 2023). These online trends have significant real-world impacts, affecting grocery store inventory, inspiring new products, and shaping conversations around health and culture (Khulbe and Pathak, 2019).

This surge of online conversation has created massive, publicly available datasets, offering researchers insights into cultural and economic shifts. A growing body of literature has established that analyzing this data with computational methods can reveal valuable information. Foundational studies have demonstrated that the language of food on social media is a powerful predictor of real-world outcomes, linking online discussions to public health statistics and geographic identities (Fried et al., 2014; Abbar et al., 2015). Subsequent research has successfully applied methods like sentiment analysis and topic modeling to understand public attitudes towards broad topics like nutrition (Saura et al., 2020), specific categories like organic foods (Singh and Glińska-Neweś, 2022), and even the psychological barriers to food adoption, such as neophobia (Shan et al., 2025).

However, while these studies provide good "snapshots" of what people are discussing, a significant gap exists in understanding the lifecycle of a trend itself. Little is known about the full lifecycle of a food trend, how it begins, gains popularity, and eventually declines. This limitation has been noted across multiple studies, where researchers acknowledge that their cross-sectional approaches cannot capture the dynamic nature of trend evolution (Cash et al., 2022; Drescher et al., 2023). Addressing this gap requires understanding historical context, sociological theories, and methodological approaches that can capture the dynamics of trends.

This review brings together the historical context, key theoretical frameworks, and current approaches for studying food trends to make the case for a lifecycle based analysis. Using the Diffusion of Innovation theory (Rogers, 1983) as a primary framework, this review will establish the foundation for a data-driven project aiming to model and predict the full lifecycle of modern food trends.

2 Background

To understand the mechanics of modern digital trends, it is important to first examine the historical and theoretical models that govern how new ideas have traditionally spread. Food trends share many characteristics with other cultural domains, such as fashion, where the spread of new ideas has long been studied. The sociological theory of fashion, articulated by Simmel (1957), provides a strong historical analogy. Simmel argued that fashion is driven by a fundamental tension between the social needs for conformity and distinction. This created a "trickle-down" effect, where an elite class introduces a new, exclusive style that is gradually imitated by the class below them. Once a style becomes widely adopted, it loses its distinctiveness, forcing the elite to innovate again, thus continuing the cycle. This perspective provides a useful analogy for early food trend diffusion, which historically relied on expert forecasts and institutional endorsements to shape popular adoption (Sloan, 2019).

The Diffusion of Innovation theory (Rogers, 1983) offers another lens for understanding how trends spread through populations. Rogers' framework models adoption as an S-curve, categorizing the population as Innovators, Early Adopters, Early Majority, Late Majority, and Laggards. Each group represents a different threshold for accepting new ideas, creating predictable patterns of adoption over time. While digital platforms have accelerated the speed of this process, they have not displaced the fundamental mechanics of diffusion (Cash et al., 2022). Instead, social media has introduced additional pathways such as "trickle-up" and "trickle-across" trends. Trickle-up trends emerge when ideas originating in smaller or niche communities gain visibility and are later adopted by mainstream population, while trickle-across trends spread laterally as different groups adopt them simultaneously across networks (Cash et al., 2022). In the context of digital food trends, the S-curve can be viewed as the measurable rise, peak, and decline of online discussions, while adopter categories are represented by different types of social media participants. Influencers and content creators for instance, would function as Early adopters in this model, amplifying new ideas to broader audiences through their established follower networks.

Cultural theories also explain why certain food trends are more appealing than the others. Pierre Bourdieu's concept of cultural capital suggests that a food trend is rarely just about taste; it also carries symbolic meaning that signals values, identity, and social position (Swartz, 1997). Recent studies confirm that fool-related discussions on social media frequently engage with themes of health, sustainability, and ethics, indicating that successful trends align with broader cultural values (Singh and Glińska-Neweś, 2022). Online discussions thus serve as spaces where cultural capital is both constructed and displayed. The success of a trend often depends on its alignment with broader cultural values. For instance, celebrity endorsements are effective not only because of the endorser's reach, but also because the cultural capital of the endorser lends credibility to the trend (Knoll and Matthes, 2016).

While theories from Simmel and Rogers explain how trends arise and spread, it is equally important to understand why trends decline. A primary driver of food trend decline exists in psychological resistance to adoption, particularly evident in the later stages of a trend's lifecycle. Food neophobia, defined as the reluctance to try unfamiliar foods, represents a barrier to trend adoption (Shan et al., 2025). When a food trend experiences substantial online influence, consumer acceptance ultimately depends on overcoming psychological hesitancies to embrace unfamiliar foods long-term. When sensory components of food (appearance, smell, or cultural unfamiliarity) activate neophobic behaviors, the trend will likely plateau and eventually enter decline (Shan et al., 2025).

This position is consistent with the cyclical models that were earlier described by theorists. Simmel's (1957) fashion analysis emphasized that cultural innovations eventually lose their uniqueness once mass consumption occurs, leading social elites to seek new styles for distinction. Similarly, food trends that initially represent newness and aspiration can reach a tipping point where they no longer hold any novelty and psychological resistance to the trend may intensify. What was once interesting can appear unappetizing when the sensory experience is reduced or challenges cultural norms of "acceptable" food. In this manner, food neophobia acts as a present-day psychological equivalent to Simmel's loss of "distinction," leading the decline phase of the trend lifecycle to arrive sooner.

Rogers's (1983) diffusion framework also helps contextualize this process. The S-curve illustrates a typical path through which innovations move through adopter categories, as previously stated. Food neophobia complicates this path by creating adoption barriers (friction points) within the diffusion process. While early adopters may lean into the novelty of new food trends, the Early and Late Majority, as defined by Rogers (1983), often face greater psychological barriers. These barriers, such as aversions to food that appears unfamiliar, unappetizing, or culturally distant, are well-documented as significant barriers in consumer acceptance (Siddiqui et al., 2023). Following initial early adoption, widespread adoption may stall, resulting in a less steep S-curve and causing the trend to have a lack of continued meaningful integration. These psychological barriers can be understood as an adaptation of Rogers' adoption categories, creating "psychological lag" where the enthusiasm of early adopters is not replicated across the broader population.

Ultimately, the decline of food trends results not only from cultural capital or market saturation, but also from psychological rejection. Research indicates that food neophobia reflects deeper evolutionary, health, and identity risk-avoidance strategies (Shan et al., 2025). Thus, decline of food trend becomes likely when factors such as familiarity, health risks, or cultural compatibility are negatively triggered. By recognizing these barriers, we gain a more sophisticated understanding of the "decline" portion of the S-curve, adding a level of psychological explanation to sociological and diffusion models of why trends fade.

3 Methodology

3.1 Methodological Approaches

The evolution of methodological approaches in food trend research reflects the increasing sophistication of both data availability and analytical techniques. One of the first systematic approaches to analyzing food discussions on social media was conducted by Fried et al. (2014), using a dataset that consisted of over 3 million tweets containing meal-related hashtags. Their methodology involved converting text data into frequency measures of specific words, then applying support vector machines to forecast state-level outcomes such as obesity, diabetes, and political affiliation. They later incorporated topic modeling using Latent Dirichlet Allocation (LDA) to identify broader thematic contexts within dietary language. This foundational work established that social media food discussions could serve as proxies for real-world health and behavioral patterns.

Abbar et al. (2015) extended this research by collecting nearly half a million food-related tweets and mapping them to calorie levels using a hand-annotated food dictionary. They developed research that provided a straightforward but unambiguous calorie-per-tweet measure and validated it against public health statistics and discovered strong correlations with obesity and diabetes rates. Beyond textual analysis, they examined reciprocal-follow and mention networks, exploring how food consumption behavior clustered and spread through social connections. This work demonstrated the importance of network analysis in understanding food trend diffusion patterns.

The field subsequently evolved toward multimodal analysis approaches. Khulbe and Pathak (2019) shifted focus toward combining geo-tagged social media images, Yelp metrics, and Google Images for analyzing New York City food trends across different cuisines. Their methodology included transfer learning using ResNet-50 for food classification, Kernel Density Estimation for identifying geographic hotspots, and Bayesian Network Models for identifying interdependencies among different cuisines. This study demonstrated that image analysis and probabilistic modeling could reveal relationships that were not visible in text alone, establishing the value of multimodal data integration.

More recent research has focused on predictive and interpretive modeling capabilities. A Reddit study by Shan et al. (2025) mapped food mentions to nutrient databases through the use of sentence embeddings, creating weighted nutrient profiles for posts. These profiles were combined with gradient-boosted tree models to predict engagement levels using SHAP (SHapley Additive exPlanations) values to determine which nutrient and linguistic features were most important for predicting popularity. This approach represented a significant advancement in understanding the content characteristics that drive trend engagement.

Ensemble modeling approaches have also emerged as sophisticated methods for trend prediction. Cash et al. (2022) use ensemble methods combining multiple models to track the rise and decline of online food trends more accurately. Their approach recognized that single-model predictions often failed to capture the complexity of trend dynamics, leading to improved performance through model combination strategies.

Contemporary methodological approaches have increasingly incorporated sentiment analysis and temporal modeling. Saura et al. (2020) utilized sentiment analysis tools like VADER and TextBlob to track how public sentiment toward nutrition-related topics evolved over time. Their approach showed that sentiment shifts often preceded changes in engagement levels, suggesting that emotional responses to food content serve as good indicators of trend lifecycle.

3.2 Limitations and Future Directions

Throughout the literature, few methodological limitations have been consistently identified. A primary concern involves the use of observational data and proxies for actual consumption behavior. Both Fried et al. (2014) and Abbar et al. (2015) acknowledge that social media usage cannot be directly equated with food consumption patterns, introducing potential validity concerns. The relationship between online engagement and real-world behavior remains an area of ongoing debate, with some researchers arguing for stronger validation approaches (Khulbe and Pathak, 2019).

Demographic representation presents another significant challenge. Khulbe and Pathak (2019) acknowledge that unobserved demographic variables likely introduce bias into their findings, as social media users may not represent broader population characteristics. This sampling bias is particularly problematic when attempting to generalize findings to entire populations or predict market-wide trends.

Campaign-based research, such as studies examining movements like Veganuary (Drescher et al., 2023), faces particular challenges in establishing causality. These studies struggle to separate the direct effects of social media campaigns from broader cultural, seasonal, or economic influences that might independently shape dietary changes. Methodological inconsistencies across studies create additional challenges for combining findings. Different researchers use varying definitions of key concepts like "food trends," "engagement," and "virality," making cross-study comparisons difficult. The lack of standardized metrics and measurement approaches has been identified as a barrier to cumulative knowledge building in the field (Cash et al., 2022).

Several important questions remain unanswered in the current literature. While studies have shown correlations between online discussions and various outcomes, reliably predicting trend trajectories remains challenging. Different modeling approaches produce varying success rates, and no clear consensus exists on the best methodological framework.

Future research could improve by combining data from multiple platforms and incorporating different types of content (text, images, videos). Additionally , linking social media data with external sources like grocery sales or restaurant menu changes could better connect online discussions to real-world consumer behavior.

4 Conclusion

Digital food trends are now a major cultural force, not just in shaping online debate but also grocery sales, restaurant offerings, and broader conversations about health and sustainability. Early studies show that social media discussions about food could predict health outcomes and economic patterns (Fried et al., 2014; Abbar et al., 2015). Later research has used images, location data, and nutritional information to understand how food trends spread (Khulbe and Pathak, 2019; Shan et al., 2025). The weight of evidence suggests that while social media discussions can predict some real-world outcomes, reliable prediction of complete patterns of trend remains limited.

Additionally, debate exists over whether correlational findings from social media data can establish causal relationships with consumer behavior, particularly given concerns about demographic representation and external validity. However, trend decline remains the least understood aspect of food trend lifecycles. While factors like cultural saturation contribute to decline, psychological barriers such as food neophobia appear to be important for explaining why some trends cannot move beyond early adopters (Shan et al., 2025). Studies of campaigns like Veganuary show the challenge of separating direct social media effects from broader cultural influences (Drescher et al., 2023).

Viewing food trends as complete lifecycles, emerging, peaking, and declining addresses the current research gap identified across multiple studies that focus only on analyzing trends at a single point in time rather than tracking how they change and evolve. This lifecycle approach, combined with data from multiple platforms and real-world validation measures, could improve both prediction accuracy and understanding of why some foods achieve sustained adoption while others quickly lose popularity.

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