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Predicting social media engagement with computer vision: An examination of food marketing on Instagram

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ABSTRACT

In a crowded social media marketplace, restaurants often try to stand out by showcasing elaborate "Instagrammable" foods. Using an image classification machine learning algorithm (Google Vision AI) on restaurants' Instagram posts, this study analyzes how the visual characteristics of product offerings (i.e., their food) relate to social media engagement. Results demonstrate that food images that are more confidently evaluated by Google Vision AI (a proxy for food typicality) are positively associated with engagement (likes and comments). A follow-up experiment shows that exposure to typical-appearing foods elevates positive affect, suggesting they are easier to mentally process, which drives engagement. Therefore, contrary to conventional social media practices and food industry trends, the more typical a food appears, the more social media engagement it receives. Using Google Vision AI to identify what product offerings receive engagement presents an accessible method for marketers to understand their industry and inform their social media marketing strategies.

1. Introduction

In the competitive food media landscape, "Instagrammable" food has become a marketing trend, with millions of visually-appealing food images posted on social media each year. Restaurants have widely embraced the value of social media, as most customers use social media (e.g., checking reviews, viewing photos) before visiting a restaurant (Lepkowska-White, 2017). Restaurants' social media use can positively influence business valuation (Kim et al., 2015), boost sales, and improve market share (Needles & Thompson, 2013). As a result, the increased use of social media by restaurants has resulted in a more crowded and competitive environment. For example, on a 2021 list of over 900 North American restaurants profiled by *Eater.com*, 92% had an active Instagram account. This is important considering that the average social media user spends 147 min per day across platforms (Statista, 2022), seeing hundreds of posts each day (Luckerson, 2015; Stewart, 2016). Consequently, one of the main challenges for food marketers is how to effectively garner engagement with their content (e.g., likes, comments, shares) in an effort to boost audience exposure on the platform and improve business performance.

The prevailing wisdom on social media is to create atypical and unique content to drive user engagement. This is consistent with extant research that has found unconventional products (Berger & Iyengar, 2013; Berger & Schwartz, 2011), unique products (Moldovan et al., 2011), surprising stories (Heath et al., 2001), and interesting news articles (Berger & Milkman, 2012) are shared more. Unsurprisingly, food marketers and restauranteurs also appear to be gravitating towards this trend. The 2022 Trend Report by Instagram suggests that young people are interested in "pushing the boundaries of food," seeking out experimentation in the kitchen (Instagram, 2021). Examples of these unique food experiences include "outlandish cakes" or molecular gastronomy. The report further suggests that Instagram is the place to embrace "exploring new territories and taking what already exists in unexpected directions." Following this logic, several restaurateurs and food bloggers indicate that they have altered their menus to prioritize visual uniqueness to ensure their food stands out on Instagram (Lee, 2017)—sometimes even at the expense of taste (Fantozzi, 2017).

Despite this prevailing wisdom, there are reasons to believe that being atypical and unique in the food landscape may not necessarily resonate with consumers. From a theoretical perspective, the idea that atypical-looking content will receive more engagement contradicts longstanding psychological research on processing fluency. Prior research indicates that visual stimuli that are more standard, typical, and familiar in appearance are liked more (Mayer & Landwehr, 2018; Reber et al.,

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2004). Applying this theory to social media suggests that images that are more easily recognized (i.e., more typical) should garner greater digital engagement. To examine what restaurants are currently doing in practice, we conducted a brief survey asking people if the food featured in the social media posts of restaurants were normal (i.e., usual, common, typical). Participants were asked to assess the typicality of food photos taken from a random sample (n = 100) of over 800 top North American restaurants on a scale from 1 to 7 (strongly disagree to strongly agree, respectively). Results indicated that the majority of photos (51.8%) received a score of 5 (somewhat agree) or less. Thus, there appears to be a lack of consensus in the social media strategy of top restaurants: some posts showcase more typical-appearing foods while others are more atypical.

This current research aims to reconcile this theoretical and practical non-consensus with the assistance of an image classification machine learning algorithm (Google Vision AI). Specifically, we use images collected from the field and analyze how the object recognition confidence scores from Google Vision AI (a proxy for object typicality) relate to engagement. In doing so, the current research makes four scholarly and managerial contributions.

First, this research provides empirical evidence for what visual characteristics of images are related to higher engagement on social media. Primarily, research examining what types of content influences engagement has focused on textual characteristics (e.g., Chevalier & Mayzlin, 2006; Chintagunta et al., 2010), with some using natural language processing algorithms to provide a more objective investigation (Pancer et al., 2019). Yet, empirical studies on the relationship between a social media post's visual characteristics and engagement are still in their infancy (for recent examples, see Kaiser et al., 2020; Li & Xie, 2020). As many social media platforms are becoming more visually oriented (e.g., Instagram, Snapchat, and TikTok), it is crucial to identify objective methods for characterizing visual content and understand how these characteristics relate to engagement.

Second, this research contributes to nascent literature that uses computer vision algorithms, like Google Vision AI, as a tool to extract marketing relevant information from social media posts. Existing research using these tools has primarily focused on examining user-generated content (Liu et al., 2020; Nanne et al., 2020). However, calls have been made to use computer vision to "make a connection to common marketing outcomes, such as brand performance or engagement (e.g., amount of likes)" (Nanne et al., 2020, p. 166). Similarly, other research has focused on high-level visual characteristics, such as the overall quality of a post, brand centrality, and whether or not there are people, faces, or brand logos present (Jaakonmäki et al., 2017; Li & Xie, 2020; Mazloom et al., 2016; Rietveld et al., 2020). The current research builds on prior work by focusing specifically on the types of product content businesses choose to post on social media, typical- or atypical-appearing. In doing so, the research validates how the Google Vision AI confidence score of an object (specifically, food objects) can be used as a proxy for how typical that item appears. The higher the confidence score, the more common and usual looking the item; the lower the score, the more likely it appears unique and atypical. Using Google Vision AI in this way extends its application, highlighting how it can be used as a methodological tool in research to provide objective measurements to better test theory and inform practice.

Third, in using Google Vision AI to determine what types of food images receive more engagement, this research contributes to scholarship on social media strategies more broadly. In a novel application of existing machine learning algorithms (Google Vision AI) and theories of processing fluency to a visual social media context, we demonstrate the value of producing and posting typical, standard, and normal appearing content to social media. In doing so, we contribute to scholarship on social media strategy by identifying the limitations of conventional social media wisdom for what types of content should receive more engagement.

Lastly, as a managerial contribution, the findings show how restaurants, food advertisers, and food media content producers can foster better engagement based on the items they choose to include on their menus and post to social media. The results indicate that, despite conventional wisdom and industry trends suggesting that restaurants do the opposite, the more typical, normal, and conventional appearing food items garner the most engagement. Therefore, in presenting these implications, we also highlight how restaurants have been encouraged to engage in a suboptimal social media strategy (i.e., posting atypical rather than typical food items).

The current paper is organized as follows. First, the theoretical development section juxtaposes two competing possibilities: the typicality of social media content is either positively or negatively related to engagement. Second, the research reports the empirical analysis of data drawn from the field and the results of an experiment. Finally, the paper discusses the findings and concludes with the theoretical contributions, managerial implications, limitations, and avenues for future research.

2. Theoretical development

Recognizing that social media platforms use ranking algorithms to give more visibility to content that has better engagement (e.g., more "likes") (Carbone, 2019), marketers must identify what types receive the most engagement so that they can tailor their content to increase their reach and exposure. In general, food is among the most popular content on social media (Tubular, 2022). However, when asking what types of foods restaurants should be producing and posting on social media to garner more engagement, the visually atypical or typical, there is theory to support both possibilities.

2.1. Conventional social media wisdom: In support of atypical food content

While social media as a marketing medium is still in its relative infancy, the last ten years has seen research aimed at helping social media marketers and content producers post content that will garner engagement. Yet, attracting attention on social media can be very competitive. For example, there are, on average, 1,500 unique posts available each time a user visits Facebook (Meta for Business, 2013), and 65,000 photos are shared on Instagram every minute (Statista, 2021). Given the sheer amount of content available, prior research suggests that content needs to be entertaining to stand out, whereby "entertaining" is often synonymous with the novel, unique, surprising, and extreme (Berger, 2014). Therefore, when it comes to posting food content, and as industry trend reports would recommend, novel and unique (i.e., atypical) looking content should be more entertaining and thus receive more engagement.

Supporting this assertion, people are more likely to talk about novel than ordinary products (Berger & Iyengar, 2013; Berger & Schwartz, 2011; Moldovan et al., 2011). Similarly, both surprising urban legends (Heath et al., 2001) and news stories (Berger & Milkman, 2012) are shared more online. Consistently, personal stories that are more extreme, thus breaking a normative standard, are discussed more frequently (Heath & DeVoe, 2005).

Like the examples above, engaging with entertaining content is believed to support an impression management motive (Berger, 2014). In the context of social media, researchers have considered liking and commenting as a form of word-of-mouth communication (e.g. Swani et al., 2013; De Vries et al., 2012), and word-of-mouth, in general, is used to portray desirable impressions (e.g., Belk, 1988; Berger & Heath, 2007; Philp & Ashworth, 2020; Philp et al., 2018). Engaging with content online is influenced by impression management because liking or commenting on a social media post is visible to others, therefore publicly stating one's preferences and identities (De Vries et al., 2012). Because of this, engaging with unique, novel, and atypical content is believed to support the general self-enhancement goal of appearing entertaining and interesting to others (Berger, 2014).

Taken together, when applied to restaurants' Instagram pages, this previous research would suggest that food offerings that are novel, unique, and atypical should garner the most engagement. This is because this type of content is visually outside the normative standard and likely to be considered more entertaining. Thus, engaging with it serves a self-enhancement impression management motive of appearing entertaining. However, much of the prior research supporting this idea relates to social media text and stories or word-of-mouth communication more generally. Yet, popular social media platforms are becoming faster and more visually oriented with videos and photos (e.g., Instagram, Snapchat, and TikTok). Thus, the expected impact of atypical-appearing food content on engagement is unclear.

2.2. An alternative perspective: In support of typical food content

Although conventional social media wisdom and industry trends would suggest greater engagement with atypical food images, applying theories of processing fluency would predict the opposite. Processing fluency is defined as “the ease with which information flows through the cognitive system” (Shimamura & Palmer, 2012, p. 151). Broadly, processing fluency argues that when presented with a new piece of information, the easier it is to understand (i.e., process), the more positive an individual feels, which subsequently increases liking of the information (Mayer & Landwehr, 2018). Specifically, “high fluency may elicit positive affect because it is associated with progress toward successful recognition of the stimulus, error-free processing, or the availability of appropriate knowledge structures to interpret the stimulus” (Reber et al., 2004, p. 366). Consistently, typical (versus atypical) stimuli are easier to process, which makes people feel positive about them in general (Posner & Keele, 1968; McClelland & Rumelhart, 1981; Smith et al., 1974).

While there is a lack of research on how the visual fluency of social media posts influences engagement, prior empirical research has investigated the influence of textual fluency. Research in this area is consistent with research on readability and comprehension in an offline context: the more readable and easier to process texts, the easier they are to comprehend and are subsequently liked more (Chall & Dale, 1995; Flesch, 1948; Gunning, 1952; Klare, 1963; Klauda & Guthrie, 2008; McLaughlin, 1969). When applying this rational to a social media context, Pancer et al. (2019) found that text posts on Facebook and Twitter that are easier to read receive more likes, comments, and shares.

Findings from research on visual fluency consistently suggest that simplicity and typicality of a visual stimulus increase visual fluency (Winkielman et al., 2003) and subsequent positive affect (Winkielman & Cacioppo, 2001). Broadly, the less visual information a stimulus contains, the easier it is to process and the more it will be liked. Moreover, it is suggested that liking will decrease when a visual stimulus becomes too complex or challenging to recognize. This process has been suggested to result from a defensive mechanism, helping people cope with stimuli that are overly intense, unknown, and potentially dangerous (Selye, 1956; Sokolov, 1963).

Relatedly, studies in cognitive psychology have found that prototypical or “average” visual stimuli are processed more easily and preferred over atypical stimuli (Posner & Keele, 1968; McClelland & Rumelhart, 1981; Smith et al., 1974). “Prototypicality refers to the extent to which a stimulus is representative of an overarching category” (Landwehr et al., 2013, p. 93). Preference for prototypical over atypical stimuli has been demonstrated across different types of visual stimuli, including brands (Janiszewski & Meyvis, 2001), color swatches (Martindale & Moore, 1988), paintings (Hekkert & van Wieringen, 1990), furniture (Whitfield & Slatter, 1979), faces (Langlois & Roggman, 1990; Rhodes & Tremewan, 1996), and even shapes (Winkielman et al., 2006).

In summary, visual fluency research suggests it is more difficult to process an atypical item, which results in negative affective feelings, such as confusion and stress. Inversely, it is easier to process a prototypical (i.e., typical) item, which results in positive affective feelings, such as pleasantness and happiness. In both cases, these positive/negative feelings subsequently bias any attitudinal judgment of the target item that caused it.

Related to social media content, prior research has emphasized the link between positive affect and engagement (Eigenraam et al., 2018; Moore & Lafreniere, 2020; Pancer et al., 2019; Pancer et al., 2022). Thus, if easier to process visual stimuli increases positive affect, it should also increase social media engagement with that content. Therefore, despite prior research (Berger, 2014) and industry trends (Instagram, 2021; Fantozzi, 2017) recommending that unique content should receive more engagement, it is instead typical-appearing food content that should garner more engagement from a processing fluency perspective.

3. Overview of studies

The empirical examination has four primary objectives and follows an inductive approach (Janiszewski & van Osselaer, 2021). The first objective is to provide evidence that the confidence score given by Google Vision AI of food objects is related to individual perceptions of food typicality. The second objective is to use field data of Instagram posts from actual restaurants to test these competing predictions for which type of food images (i.e., typical or atypical) receive the most engagement. The third objective is to replicate the findings from the empirical analysis of data from the field in a controlled experimental setting. The last objective is to provide evidence for the underlying mechanism of this effect.

4. Study 1

Study 1 employed data mining and content analysis techniques to analyze the social media posts of restaurants on Instagram. A proxy for food typicality, along with other visual and textual variables that could influence engagement, were gathered. Using those variables, various regression models were tested to predict the number of likes and comments based on food typicality.

4.1. Sample and dataset creation

The dataset consisted of Instagram posts from various top restaurants across the United States, Canada, and England (see Fig. 1 for the data collection process). The food and dining website *Eater* (eater.com), which is a guide for dining and drinking (Kludt, 2014), was used to build the restaurant sample. Each season, *Eater* releases “The 38 Essential Restaurants” for each of their focal cities, which identifies the 38 must-try restaurants across different neighborhoods, budgets, and cuisines (McCarthy, 2021). A manual search identified 871 restaurants with active Instagram accounts from the restaurants listed in Eater’s Summer 2021 guide for their 26 focal cities. Using the Instagram Graph API, we scraped the number of followers each account had, as well as the number of likes and comments, the image URL, post date and time, and the text-based caption of, at most, the twelve most recent posts for each account. This resulted in data from 10,173 posts.

4.1.1. Independent variable creation and validation: Food typicality

Google Vision AI was used to analyze the image of each post. Google Vision AI uses pre-trained machine learning models to understand images (Google, 2019a) by providing different features such as image labelling; face, logo, and landmark detection; optical character recognition (OCR); and detection of explicit content (Google, 2019b). Visual recognition algorithms, like this, are designed and trained in a similar manner to how humans learn to identify and categorize their visual surroundings—through trial and error (Lewis-Kraus, 2016). Specifically, Google Vision AI processes an uploaded image file and detects a number of “objects” and “labels,” providing a confidence score for each. The identified objects will have a confidence score ranging from 0.50 = little confidence and 1.00 = very high confidence (Google, 2019a). Google

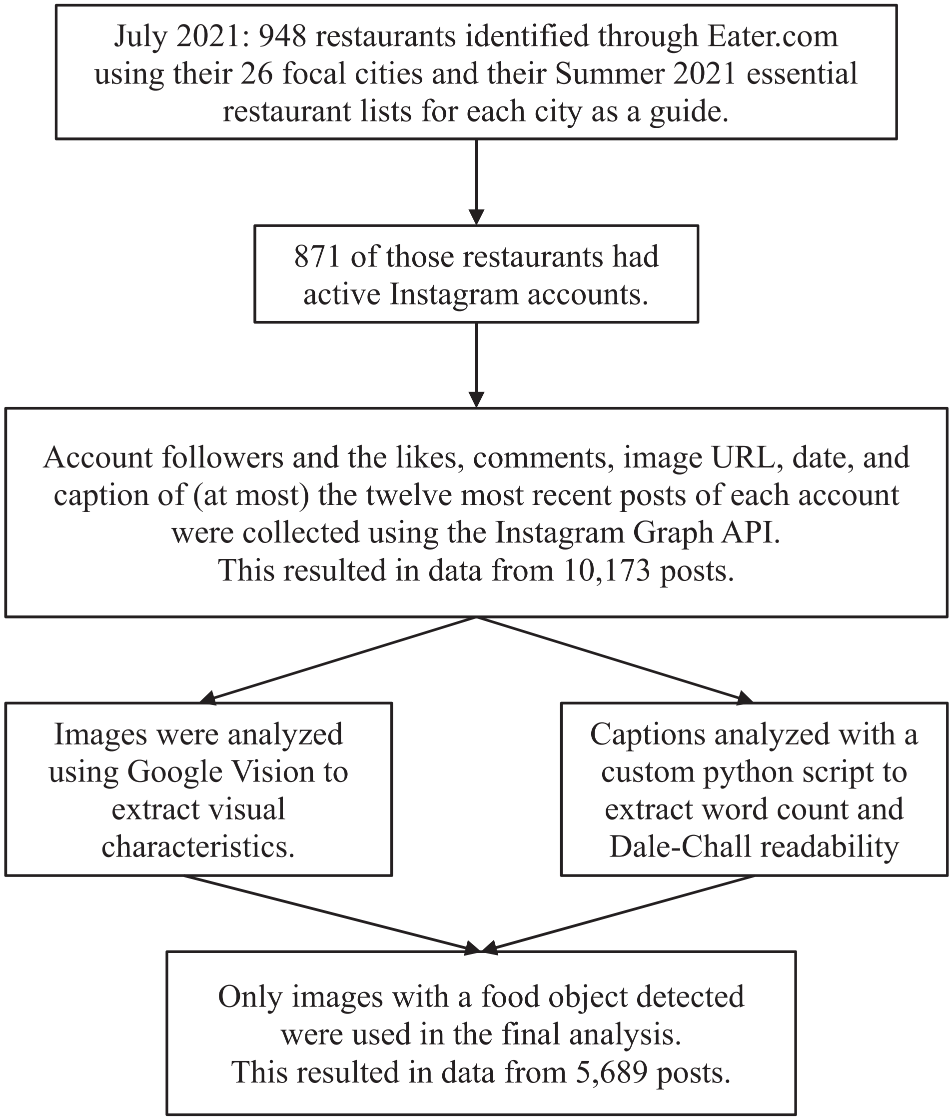

Fig. 1. Data collection process.

Vision AI relies on a proprietary database of images previously identified and labelled by humans. Then using their internal machine learning framework (TensorFlow.org), a deep learning neural network identifies objects and labels that have at least a 50% confidence score. An "object" is the higher order category, and the "label" represents more nuanced details of the objects being detected.

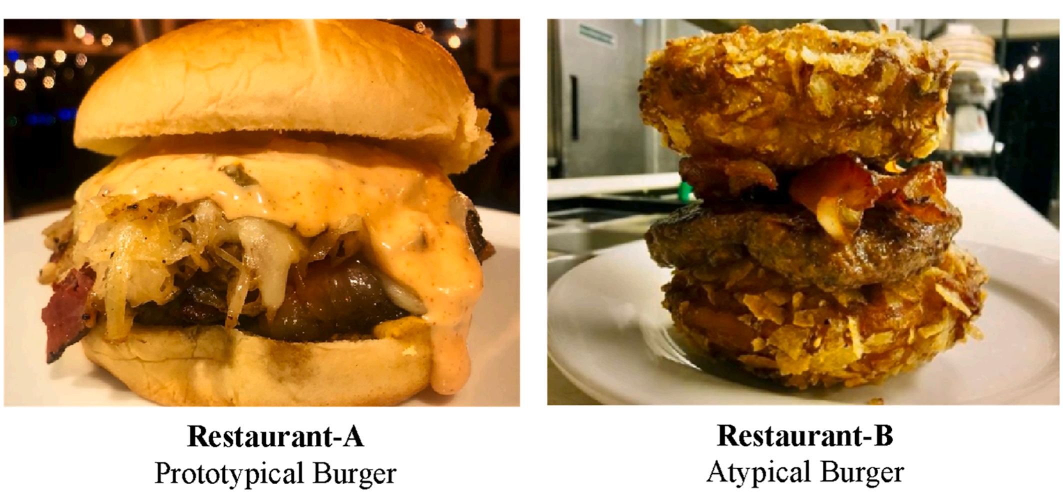

Fig. 2. Sample prototypical and atypical food images.

For example, in Fig. 2, Google Vision AI would detect the object of "food" for both with varying confidence scores. Restaurant-A's burger is arguably fairly standard and prototypical looking. Subsequently, it was recognized by Google Vision AI as a food object with a confidence score of 78%. Restaurant-B's burger is slightly more atypical, arguably not looking like a standard burger. Subsequently, it received a confidence score of 66%. Given the focus on assessing food image typicality and the influence on engagement, we only analyzed posts with "food" as at least one of the objects detected. This resulted in a final dataset of 5,689 posts.

Based on how Google Vision AI functions and is trained in image detection, as described above, we used the average confidence score of food objects in each Instagram post as a proxy for food typicality as the independent variable. Given that Google Vision AI draws from a database of images previously tagged by humans and then assigns a confidence score for how closely it matches that tag, arguably the higher the confidence score, the more typical the food should appear and be. This is because the image should have characteristics that closely match multiple prototypical standards used in training the computer vision algorithm. Similarly, the lower the confidence score, the more atypical the food should be.

To validate this, human coders evaluated the typicality of a random sample of 100 images of food from the final dataset. Each post was already labelled to have at least one food object from the Google Vision AI output and thus had an average confidence score of these food objects. Following a similar human coding validation procedure of prior computer vision research (Nanne et al., 2020), 149 participants (40.3% female; $M_{\text{age}} = 37.26$; $SD_{\text{age}} = 10.50$) recruited from Amazon Mechanical Turk were randomly exposed to ten posts. Participants were informed that the images were from the Instagram accounts of different restaurants across North America. Their task, as instructed, was to "*answer a single question for how normal (*i.e.*, usual, common, typical) you think the meal in the image appears.*" Participants responded how much they agreed with the statement, "this is a picture of a normal looking meal," on a 7-point scale (1 = Strongly Disagree, 7 = Strongly Agree). To enhance validity, each post was evaluated by, on average, 15 individual coders. A linear regression analysis was conducted with the average food object confidence score from Google Vision AI as the dependent variable and average typicality rating for each post as the independent variable. As expected, the results evidenced that the typicality rating by human coders is positively related to the Google Vision AI food object confidence score ($\beta = 0.04$, $t(100) = 5.36$, $p < .001$; $R^2 = 0.23$). These results substantiate the assertion that the confidence score given to food objects by Google Vision AI is positively related to the visual typicality of a food image and can be used as a proxy for food typicality. This score served as the independent variable in the analysis.

4.1.2. Dependent variable: Social media engagement

Aligned with prior research examining social media engagement (Tafesse & Wien, 2018; Kim & Yang, 2017; Pancer et al., 2019; Pancer et al., 2022), the number of likes and comments a post receives are the dependent variables. Other engagement metrics on Instagram include "saves," "story replies," "profile clicks," and "shares" (Hitz, 2019); however, these metrics are not made publicly available using the Instagram Graph API. Of the 5,689 posts from the dataset, 5,687 posts received at least one like, and 4,882 received at least one comment.

4.1.3. Control variables

The research also included various control variables, including 1) *visual perception variables* (e.g., number of objects, face detection, photo quality), 2) *timing of post variables* (e.g., days since post), 3) *caption-specific variables* (e.g., word count, readability), and 4) *account-specific variables* (the number of account followers).

1) *Visual perception variables.* To control for image complexity, the total number of food objects, number of objects in general, and number of labels are each controlled for. Whether a face was detected was also controlled for, as photos with faces have been found to affect engagement on Instagram (Bakhshi et al., 2014; Li & Xie, 2020). Additionally, prior social media research supports that image quality influences engagement (Li & Xie, 2020). We recognize that poorer quality photos may also receive lower food object confidence scores, as prior evidence suggests that Google Vision AI can be influenced by distortion (Hosseini et al., 2017). Therefore, it is possible that it is not the food typicality that influences engagement, but the overall quality of the image. To control for this, we analyzed each image using the Blind/Referenceless Image Spatial Quality Evaluator algorithm, which calculates an overall image quality using the visual aspects of a photo (e.g., contrast, brightness, blur, and colorfulness). This algorithm has been validated against other image quality algorithms and human coders (Mittal et al., 2011).

2) *Timing of post variables.* Days since the post was made, the day of the year, and the day of the week were recorded to control for variance associated with the amount of time the post has been available to engage with and any timing effects.

3) *Caption-specific variables*. Regarding the text caption of each post, both the word count (i.e., post length) and the Dale-Chall readability score (Chall & Dale, 1995) were calculated using a custom Python script and used as control variables. The Dale-Chall readability score is widely used in linguistics research (DuBay, 2004). It identifies the percentage of words in a text that are outside a list of 2,950 words that are known by 80% of Grade 4 students. The higher the score, the higher reading level required to understand the text. Both this readability score and word count were used as controls as they have both been shown to affect social media engagement (Pancer et al., 2019).

4) *Account-specific variable*. The number of followers for each account was also controlled for, as it is expected that the more followers an account has, the more opportunities a post has to receive engagement.

4.2. Regression analysis

See Table 1 for descriptive statistics. Several posts generated a disproportionately high number of likes and comments, which positively skewed the data. Thus, to account for this, we calculated the natural logarithm of both the number of likes and comments as dependent variables in a series of OLS regression analyses. Both likes and comments had a 0.71 ($p < .001$) correlation (see Table 2), which demonstrates that these variables are related.

We first regressed likes and comments on food typicality (i.e., the averaged confidence score given to food objects as indicated by Google Vision AI), in a simple OLS regression (Tables 3–4; Model 1). This model

Table 1
Study 1 – Summary Statistics.

		Mean	SD
Outcome variables			
	Number of Likes	297.33	577.10
	Number of Comments	7.69	20.76
	Likes (log-transformed)	2.18	0.50
	Comments (log transformed)	0.67	0.46
Predictor variables			
	Food Typicality [i]	0.71	0.08
Visual perception controls			
	Number of Food Objects	1.79	1.71
	Number of Objects	3.03	3.13
	Faces	0.96	1.29
	Quality	46.13	13.85
Time controls			
	Days Since Post	96.63	257.29
Caption controls			
	Word Count	37.86	35.84
	Dale-Chall Readability Score	6.70	3.28
Account-specific controls			
	Number of Account Followers	17,049.61	38,926.91
Sample: 5,689			

Note. [i] Average Google Vision AI Confidence Score of Food Objects.

Table 2
Study 1 – Correlation Matrix.

	Variable	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
1.	Likes	0.71 **	0.10 **	−0.02	−0.03 *	−0.04 **	0.05 **	−0.03 **	−0.23 **	0.10 **	0.07 **	0.39 **
2.	Comments		0.03 *	−0.02	−0.02	−0.05 **	0.04 **	0.04 **	−0.07 **	0.13 **	0.01	0.24 **
3.	Avg. Conf. of Food Objects			−0.19 **	−0.35 **	0.07 **	−0.06 **	0.01	−0.06 **	0.01	0.09 **	0.01
4.	Food Objects				0.69 **	0.13 **	0.04 **	0.05 **	0.04 **	0.03	−0.05 **	0.01
5.	Objects					0.13 **	0.11 **	0.05 **	0.06 **	0.05 **	−0.08 **	−0.01
6.	Labels						−0.02	−0.09 **	−0.01	−0.02	−0.00	−0.02
7.	Faces							−0.08 **	−0.02	0.04 **	−0.01	−0.00
8.	Quality								−0.01	0.02	−0.01	0.00
9.	Days Since Post									−0.08 **	−0.04 **	−0.11 **
10.	Word Count										−0.03	0.02
11.	Dale-Chall Readability											−0.00
12.	Account Followers											

Note. Engagement outcomes are log-transformed; ** $p < .01$; * $p < .05$.

revealed a significant effect on likes ($F(1,5685) = 54.77$, $p < .001$, $R^2 = 0.010$) and comments ($F(1,4880) = 3.90$, $p = .048$, $R^2 = 0.001$), where food typicality was a significant predictor for both likes ($\beta = 0.636$, $p < .001$) and comments ($\beta = 0.169$, $p = .048$). These results provide evidence to support that the more typical a food appears on social media, the more engagement it will receive in the form of likes and comments.

To demonstrate the robustness of this effect, we then tested four additional models, each stepping in new categories of control variables. In Model 2, we introduced all the visual perception controls and remained significant (likes: $F(10,5676) = 15.21$, $p < .001$, $R^2 = 0.026$; comments: $F(10,4871) = 5.45$, $p < .001$, $R^2 = 0.007$) where food typicality was a significant predictor for both likes ($\beta = 0.704$, $p < .001$) and comments ($\beta = 0.213$, $p = .022$) (Tables 3–4; Model 2). In Model 3, we introduced timing of post variables. The effect of food typicality remained significant for both engagement variables (likes: $\beta = 0.654$, $p < .001$; comments: $\beta = 0.207$, $p = .026$) (Tables 3–4; Model 3). In Model 4, we introduced caption-specific control variables known to influence engagement (Pancer et al., 2019) and food typicality remained significant for both engagement variables (likes: $\beta = 0.617$, $p < .001$; comments: $\beta = 0.189$, $p = .040$) (Tables 3–4; Model 4). Finally, in Model 5, we introduced the account-specific control of how many followers the account had at the time of data collection. Again, the effect of food typicality remained significant for both engagement variables (likes: $\beta = 0.585$, $p < .001$; comments: $\beta = 0.175$, $p = .050$) (Tables 3–4; Model 5).

Overall, contrary to what conventional social media wisdom would suggest, results showed that more typical-appearing foods are more likely to receive social media engagement. Although these results are beneficial, given they are real-life data pulled from the field and based off the objective analysis of machine learning output, they do not address what might be underlying this effect. We address this in Study 2.

5. Study 2

As a further test of robustness and exploration into the underlying mechanism of the results found in Study 1, we conducted a follow-up experiment. Since Study 1 showed evidence that typical (versus atypical) foods receive more engagement, it is predicted that this is because typical-appearing foods are easier to visually process, which thus elevates positive affect, and carries over to positively influence engagement with the content (e.g., likes and comments). Visual fluency research argues that seeing familiar, simpler stimuli make people happier than seeing unfamiliar and confusing items because the mind can more easily process those items (Reber et al., 2004). This happiness then biases subsequent attitudinal judgments towards the target stimulus to be more positive (Mayer & Landwehr, 2018; McClelland & Rumelhart, 1981; Posner & Keele, 1968). In the context of social media, prior research has identified that positive affect should lead to greater social media engagement (Eigenraam et al., 2018; Moore & Lafreniere, 2020; Pancer et al., 2019; Pancer et al., 2022). In the current experiment, we manipulated the typicality of food photos posted by restaurants on Instagram and observed the influence on engagement intentions and affect. We predict that engagement intentions will be higher for typical (versus atypical) foods and that this effect is driven by elevated positive affect.

5.1. Design and procedure

219 participants (38.1% female; $M_{age} = 36.85$; $SD_{age} = 10.49$) recruited from Amazon Mechanical Turk participated in a between-subjects single factor experiment with two conditions (low versus high typicality). Four food image posts were used from the sample of 100 Instagram posts used in the human coder analysis from Study 1. Using the Google Vision AI food object confidence score, two posts were drawn at random from the bottom quartile (low typicality) and two from the top quartile (high typicality) (see Fig. 3 for stimuli). Participants were then randomly exposed to one of these four images and asked to imagine

Table 3
Study 1 – Effect of Food Typicality on Likes (log-transformed).

	OLS Regression, Likes									
	(1)		(2)		(3)		(4)		(5)	
Food Typicality [i]	0.636	***	0.704	***	0.654	***	0.617	***	0.585	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Visual Perception Controls										
Number of Food Objects			−0.002		−0.003		−0.003		−0.006	
			(0.650)		(0.524)		(0.520)		(0.222)	
Number of Objects			0.001		0.003		0.003		0.003	
			(0.760)		(0.291)		(0.344)		(0.268)	
Number of Labels			−0.002	**	−0.002	**	−0.002	**	−0.001	*
			(0.004)		(0.001)		(0.003)		(0.010)	
Faces			0.021	***	0.018	***	0.016	**	0.017	***
			(0.000)		(0.000)		(0.002)		(0.000)	
Brightness			−0.001	**	−0.001	**	−0.001	*	0.035	
			(0.009)		(0.007)		(0.011)		(0.331)	
Contrast			−0.003	***	−0.003	***	−0.003	***	0.537	**
			(0.000)		(0.000)		(0.000)		(0.000)	
Colorfulness			−0.004	***	−0.003	**	−0.003	**	−0.003	**
			(0.000)		(0.002)		(0.006)		(0.003)	
Blur			0.000	***	0.000	***	0.000	***	0.000	***
			(0.000)		(0.000)		(0.000)		(0.000)	
Quality			0.000		0.000		0.000		0.000	
			(0.688)		(0.615)		(0.680)		(0.538)	
Timing of Post Controls										
Days Since Post					0.000	***	0.000	***	0.000	***
					(0.000)		(0.000)		(0.000)	
Day of Year					0.000		0.000		−0.000	
					(0.258)		(0.188)		(0.381)	
Day of Week					0.012	**	0.013	***	0.015	***
					(0.001)		(0.000)		(0.000)	
Caption-Specific Controls										
Word Count							0.004	***	0.004	***
							(0.000)		(0.000)	
Dale-Chall Readability							0.019	***	0.018	***
							(0.000)		(0.000)	
Dale-Chall × Word Count							0.000	***	0.000	***
							(0.000)		(0.000)	
Account-Specific Controls										
Account Followers									0.000	***
									(0.000)	
Constant	1.726	***	2.059	***	2.028	***	1.849	***	1.778	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
R^2	0.010		0.026		0.074		0.091		0.224	
R^2 Change	–		0.017	***	0.048	***	0.017	***	0.133	***

Note. Reporting standardized beta coefficients with *p* values in parentheses; * = $p < .05$; ** = $p < .01$; *** = $p < .001$; [i] Average Google Vision AI Confidence Score of Food Objects.

coming across the images while scrolling through Instagram. Assigning participants at random to see one of the possible photos reduces the possibility that the results would be stimulus dependent.

Participants rated their engagement intentions (Pancer et al., 2022; adapted for an Instagram context) (anchored: 1 = Extremely unlikely; 7 = Extremely likely – “Click the ‘like’ button”; “Comment on this post”; “Share this on your own feed”; “Share this with specific friends on Instagram”; “Follow this page”). These items were averaged to create an engagement index (α = 0.95). Participants also responded to four bipolar items on a 9-point scale which were averaged to capture their affective state (Noseworthy et al., 2014; “I currently feel…” unpleasant/pleasant; positive/negative [reversed], sick/fine, sad/happy; α = 0.81).

5.2. Results and discussion

Collapsing the two low typical and two high typical conditions, we performed independent sample t-tests with the low and high typicality conditions. Supporting the predictions, results showed that participants exposed to a typical food image reported higher engagement intentions (M_{high} = 4.09, SD = 1.85) and higher affect (M_{high} = 7.05, SD = 1.26) than compared to the low typicality condition (engagement: M_{low} = 3.33, SD = 2.01; $t(217)$ = 2.93, p =.002, Cohen’s d = 0.40) (affect: M_{low} = 6.03, SD = 1.94; $t(217)$ = 4.60, p <.001, Cohen’s d = 0.62). The significant result of engagement being higher for food images that are more typical replicate the findings of Study 1.

We also conducted a mediation analysis to examine the indirect effect of food typicality (0 = low typicality, 1 = high typicality) on the likelihood to engage with the post on Instagram through affect using a PROCESS model (Model 4, 10,000 draws; Hayes, 2017). Further supporting the predictions, the indirect effect of food typicality on engagement intentions through affect was significant (β = 0.34, SE = 0.11, 95% CI = [0.154, 0.576]), (see Fig. 4).

These results replicate the empirical analysis of data drawn from the field of Study 1 and support the prediction for the positive role of affect in mediating this effect. The indirect relationship of food image typicality on social media engagement through positive affect suggests a processing fluency mechanism. This is because more typical (versus atypical) items are easier to mentally process, and thus people are likely to feel happier when visually exposed to such items (e.g., Reber et al., 2004). As we predicted and demonstrated, this increased positive effect spills over into social media engagement intentions, thus elevating engagement towards more typical content in the context of food posted on Instagram by restaurants.

Table 4
Study 1 – Effect of Food Typicality on Comments (log-transformed).

	OLS Regression, Comments									
	(1)		(2)		(3)		(4)		(5)	
Food Typicality [i]	0.169	*	0.213	*	0.207	*	0.189	*	0.175	*
	(0.048)		(0.022)		(0.026)		(0.040)		(0.050)	
Visual Perception Controls										
Number of Food Objects			−0.002		−0.002		−0.002		−0.003	
			(0.669)		(0.679)		(0.757)		(0.502)	
Number of Objects			0.000		0.001		−0.001		0.000	
			(0.958)		(0.821)		(0.831)		(0.885)	
Number of Labels			−0.002	***	−0.002	***	−0.002	**	−0.002	**
			(0.001)		(0.001)		(0.003)		(0.007)	
Faces			0.015	**	0.014	**	0.012	*	0.013	**
			(0.005)		(0.006)		(0.017)		(0.010)	
Brightness			0.000		0.000		0.000		0.000	
			(0.248)		(0.238)		(0.219)		(0.227)	
Contrast			−0.001	*	−0.001		−0.001	*	−0.001	
			(0.026)		(0.053)		(0.027)		(0.102)	
Colorfulness			0.000		0.000		0.000		0.000	
			(0.669)		(0.829)		(0.823)		(0.740)	
Blur			0.000		0.000		0.000		0.000	
			(0.110)		(0.119)		(0.130)		(0.070)	
Quality			0.001		0.001		0.001		0.001	
			(0.124)		(0.111)		(0.111)		(0.126)	
Timing of Post Controls										
Days Since Post					0.000	***	0.000	***	0.000	*
					(0.000)		(0.000)		(0.012)	
Day of Year					0.000	*	0.000	*	0.000	***
					(0.019)		(0.026)		(0.000)	
Day of Week					−0.004		−0.002		−0.001	
					(0.305)		(0.522)		(0.771)	
Caption-Specific Controls										
Word Count							0.003	***	0.003	***
							(0.000)		(0.000)	
Dale-Chall Readability							0.007	**	0.007	**
							(0.005)		(0.006)	
Dale-Chall × Word Count							0.000	***	0.000	***
							(0.000)		(0.001)	
Account-Specific Controls										
Account Followers									0.000	***
									(0.000)	
Constant	0.546	***	0.659	***	0.727	***	0.626	***	0.583	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
R^2	0.001		0.009		0.014		0.031		0.086	
R^2 Change	–		0.008	***	0.005	***	0.017	***	0.055	***

Note. Reporting standardized beta coefficients with *p* values in parentheses; * = $p < .05$; ** = $p < .01$; *** = $p < .001$; [i] Average Google Vision AI Confidence Score of Food Objects.

6. General discussion

Results of an empirical analysis of data collected from the field and an experiment showed that the typicality of food images posted on Instagram by restaurants leads to more social media engagement (i.e., likes and comments). In a novel utilization of the Google Vision AI machine learning algorithm, this research finds that the confidence score given to food objects (a proxy for food typicality as validated by human coders) positively relates to engagement. This finding was replicated in an experiment, which provided evidence that this effect can be explained by processing fluency—typical-appearing foods are easier to mentally process and thus elevate positive affect in comparison to more unique, atypical-appearing foods. These findings have several theoretical, methodological, and practical implications, as well as opportunities for future research.

6.1. Theoretical implications

At the core, this research provides two primary theoretical contributions. First, this research contributes to the growing literature on visual characteristics that influence social media engagement. Existing research in this nascent domain has largely focused on understanding user-generated content (Liu et al., 2020; Nanne et al., 2020), or how broad visual characteristics, such as image quality, brand centrality, and presence of people, faces, or brand logos influence engagement (Jaakonmäki et al., 2017; Li & Xie, 2020; Mazloom et al., 2016; Rietveld et al., 2020). The current research contributes to this emerging domain by further analyzing the visual characteristics and investigating how the typicality of objects posted on social media relates to engagement. Demonstrating how typicality influences engagement extends prior work by highlighting the nuances and specificity of visual factors that can influence engagement, which goes beyond the mere presence of certain categories of objects and instead identifies the typicality of images within a category of objects (i.e., food). Future research should continue to explore the visual aspects of social media content and its relation to engagement.

By investigating how image typicality relates to engagement, the research also contributes to a broader understanding of social media marketing. Specifically, conventional theories related to social media has emphasized that content should to be entertaining to attract engagement, whereby "entertaining" has been synonymous with unique, distinct, and atypical (Berger, 2014). Applied to the food industry, this would mean that foods that appear more atypical should garner more engagement. However, the results showed that more typical foods, not atypical foods, receive more engagement. This challenges prior work by highlighting that it is not always the unique and

Fig. 3. Study 2 stimuli [a] Average Google Vision AI confidence score of food objects.

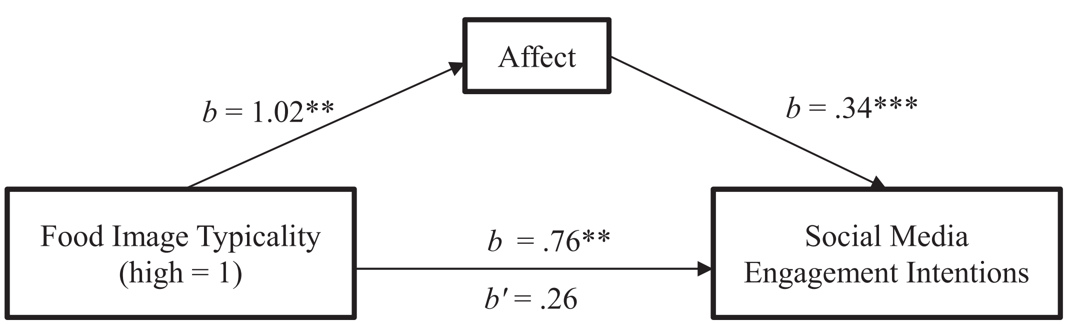

Fig. 4. Study 2 mediation analysis *Note*. Unstandardized betas are reported with superscripts: *p <.05; ** p <.01; ***p <.001.

atypical content that receives more engagement. Instead, social media users appear to prefer the more typical and normal appearing foods. Results of the experiment support a fluency mechanism (Reber et al., 2004), where an easier to process stimulus can elevate positive affect and increase subsequent liking. While this is against conventional theories of what content is predicted to garner engagement (Berger, 2014), more recent social media research is aligned with the findings. For example, Pancer et al. (2019) found evidence that stories that are easier to read are positively related to engagement on Facebook and Twitter as it elevates affect. Given the fast-paced nature of social media where users quickly scroll through content, an individual's decision to engage is likely driven by these automatic processes, influenced by an individual's affective state (Pancer et al., 2019; Pancer et al., 2022). While the goal of the current research was not to empirically demonstrate the circumstances that influences consumers to engage more with either typical or atypical content, future research should explore these boundaries and possible moderators that push a user to prefer one or the other.

6.2. Methodological implications

This work also contributes methodologically by demonstrating how Google Vision AI object confidence scores can be used as a proxy for item typicality. Given that Google Vision AI, along with other computer vision algorithms, have been designed and trained in a similar way to how humans come to identify and categorize their visual surroundings (Lewis-Kraus, 2016), the confidence score given to an object (after controlling for image quality) helps to assess how prototypical that particular object should be. Results of the human-coder analysis provide support for this. Specifically, foods that were rated as more typical and normal in appearance by human coders were also more likely to have a higher food object confidence score by Google Vision AI. We subsequently used the Google Vision AI food object confidence score as a proxy for food typicality, finding that it is positively related to social media engagement. This method highlights how Google Vision AI can be used in research beyond simple object detection, such as brands or faces (Li & Xie, 2020; Rietveld et al., 2020) or capturing image quality (Li & Xie, 2020). Examining how this object confidence score relates to various performance metrics can provide considerable insight beyond social media and into other domains, such as advertising and product design.

6.3. Practical implications

The results of this current research point to two clear practical implications. First, as an extension of the methodological implication, we demonstrate how using Google Vision AI to capture item typicality is an accessible method for both researchers and practitioners. For researchers, it is demonstrated how using a pre-trained existing machine learning algorithm can be applied in novel ways to help advance theory. Specifically, using Google Vision AI object confidence scores as an independent variable provides an objective way to measure an inherently subjective characteristic (i.e., object typicality). Similarly for practitioners, who may not have the resources or knowledge to train their own machine learning algorithms (De Luca et al., 2021), the current research shows how they can use Google Vision AI to easily identify what types of product content posted on social media within their industry receives the most engagement. They can then continue to use Google Vision AI when deciding what content to post to social media themselves, ensuring that the content matches the characteristics that are seen as optimal from within their industry.

Second, and specifically for the food industry, the results point to a specific product and content strategy for restaurants. That is, restaurants should focus on producing and posting more typical-appearing food photos. Interestingly, this goes against conventional social media research and industry trends. Content producers have instead been consistently guided to create and post atypical content. For restaurants, this meant prioritizing visual uniqueness with their food (Lee, 2017) in an attempt to be more "Instagrammable" (Brown, 2016). Instagram similarly noted that "pushing the boundaries for Food" is a trend for 2022 (Instagram, 2021). Yet, the results showed that these strategies are likely suboptimal. Instead, it is typical-appearing foods, rather than atypical foods, that receive more engagement. Thus, a clear managerial implication for restaurants and food marketers is to produce and promote more typical-appearing foods on social media to attract higher engagement.

6.4. Limitations and future research

There are several limitations to consider that point to possible areas of future research. First, the current research sought to examine immediate engagement with firm-generated content. Thus, it did not examine the influence of this content on specific portions of the population, such as influencers and food bloggers, or downstream success, such as sales. Additionally, the effect of food typicality on users with specific personality characteristics was not analyzed. For example, prior research suggests that people with a predisposition for uniqueness are more motivated to portray that unique identity through consumption (Simonson & Nowlis, 2000) and, therefore, may be inclined to engage more with unique appearing content. Future research should examine these possibilities to identify other effects and boundary conditions.

In interpreting the results, we were also cognizant of the effect sizes. The effect size of the Google Vision AI confidence score is stronger on likes than the number of comments. This is possible because "liking" a social media post is an implicit affective response, whereas commenting is more cognitive and requires more thought (Kim & Yang, 2017). Therefore, "liking" a post should be more strongly influenced by affective biases—like those spawned by processing fluency. Future research could explore this further, seeking to disentangle the types of content that spur likes and the types of content that influence comments. To date, however, social media engagement research has more commonly treated engagement metrics as being typically influenced in the same way by the same factors (Pancer et al., 2019; Pancer et al., 2022).

Finally, the current research focused on the restaurant industry and the prototypicality of food images posted to social media in this context. It is well understood that different factors impact engagement in different ways depending on the industry and context (Bernritter et al., 2016; Cao et al., 2020; Kong et al., 2021; Liu et al., 2021; Ngai et al., 2016; So et al., 2021; Swani & Milne, 2017). Therefore, while utilizing Google Vision AI to identify how product typicality relates to engagement can be used in other industries; the current research cannot provide specific insights into what content to post in these industries. For example, atypical products may receive more engagement in an industry that values innovativeness, such as technology. Future research can take the same technique utilized in the current research and examine such a possibility.

CRediT authorship contribution statement

Matthew Philp: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jenna Jacobson:** Writing – review & editing, Writing – original draft, Conceptualization. **Ethan Pancer:** Writing – review & editing, Methodology, Funding acquisition, Formal analysis, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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