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Visual Attractiveness of Food Images: Exploring User Perception

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The visual representation of food holds a significant influence on online food recommender systems. A slight change in the primary visual feature can nudge human decision-making whether the food is healthy or not. This study aims to understand how users perceive the attractiveness of food images. In an online experiment involving 192 participants, users provided ratings on a scale from 1 (very unattractive) to 7 (very attractive) and provided textual assessments of the visual attractiveness of food images. The findings emphasize a robust correlation between fundamental visual features and image attractiveness. In contrast, most studied user characteristics were less significant in predicting how the food image is attractive. On the other hand, food image dimension, image appearance, and perceived healthiness are significantly related to how users rate and judge food images.

Additional Key Words and Phrases: Personalization, Health, Food recommendations, Digital nudges, Nutrition labels

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1 INTRODUCTION

Food perception and consumption involves a lot of human affective processes. Besides nutritional goals, food preferences are driven by motivations related to hedonic goals, such as related to the taste of meal.

Food preferences are strongly driven by visual appearance. Meals of which a person knows it is taste but which looks, for example, 'disgusting', is rarely consumed to the affective associations. Moreover, an internet-sourced recipe with appealing ingredients but accompanied by an unattractive photo is unlikely to be rated highly.

User preferences can be steered by navigating the visual characteristics of images. Not only by the composition of the meal components, but also through the image quality. Different features underpin images, such colorfulness, etc. etc.

1.1 Research Questions

- RQ1 : To what extent different visual features will predict image attractiveness?
- RQ2 : What user characteristics, including demographics, food knowledge, and eating goals, influence food image attractiveness?
- RQ3 : What determines user ratings in the context of food image pictures?

2 RELATED WORK

The rapid increase in obesity and the increase in online portals for making food choices, such as what food to eat, recipes to try, and what restaurants to dine in, encourage researchers to explore the food decision domains. However, the visual appearance of food images in the digital sphere received limited research attention. As it is well established in the literature [1, 7], there is a biological connection between food photography and human behavior. Notably, the act of viewing images of indulgent foods triggers mental simulations, subsequently stimulating human appetite. In that direction, Starke et al. showed how visually appealing images lead to more healthy food choices in online user experiments. The large study in [14] explored how visual features influence appreciated and less appreciated recipes through offline experiments using various machine learning algorithms and online user experiments. On the other hand, Yum-me [13] proposed a personalized food recommender system with a main goal to meet individuals' nutritional expectations, dietary restrictions, and fine-grained food preferences using food image comparison that leads to 42% improvement in recommendation acceptance rate.

2.1 Contribution

Showing the importance of visual features in human food choices, we extend the state of the art work by studying the main features that influence human perception of food images. As the main goal to fin

3 METHODOLOGY

The main aim of this study is to gain insights into the user perception of food images. To achieve this objective, the following section outlines the proposed methodology.

3.1 Dataset

To design our study, we utilized a dataset sourced from the well-known website AllRecipes.com, consisting of 200 recipes. Given the study's focus on analyzing image pictures, we deliberately selected half of the dataset with high-quality and visually appealing food images, while the remaining half comprised images with a less-quality appearance.

3.2 System Design and participants

We proposed a straightforward system design with user consent acquisition as the system introduction. Subsequently, participants furnish crucial demographic information. The following step involves the system's collection of questionnaire responses concerning the user knowledge that measure the user food knowledge and cooking skills, which were validated in previous studies [4, 5, 8], followed by inquiries related to the user's profile [3]. Moving forward, users proceed to the rating and judgment phase, wherein each participant assesses and evaluates the visual appeal of 12 images. Finally, participants respond on a 5-point Likert scale to the food image dimensions questionnaire [14].

We employed the Prolific crowdsourcing platform to recruite participants for our study, remunerating them with 1 GBP. A total of 193 individuals actively participated in the study.

4 RESULTS

To answer the research questions, we employed the linear modeling to understand principal impacts of image attributes and user characteristics on measures of image attractiveness derived from user ratings

4.1 RQ1: Food image visual features and attractiveness

We first start to evaluate the impact of the image itself on user perception and attractiveness, we extracted diverse low-level visual features. Subsequently, we conducted a linear regression analysis to predict attractiveness based on these extracted features. The presented results in Table 1, reveal that several image features play a significant role in predicting the attractiveness of a food image [F(8, 2100)= 32.66]. Specifically, Colourfulness, Brightness, Naturalness, and Entropy demonstrate a positive association with image attractiveness. In contrast, Saturation, Sharpness, and RgbContrast reveal a negative influence on image attractiveness.

Table 1. Linear regression model predicting the visual attractiveness rating for recipe images based on low-level image visual features. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Basic Image Features	$\beta(S.E)$
Constant	-6.88 (1.24)***
Colourfulness	6.72 (1.52)***
Brightness	2.13 (0.15)***
Naturalness	1.91 (0.53) ***
Entropy	1.02 (0.15)***
Saturation	-3.97 (1.02)***
Sharpness	-1.18 (-1.18)*
RgbContrast	-1.78 (3.80)
Contrast	7.40 (11.10)
R^2	0.110***
RMSE	1.753

Going beyond basic visual image features, we harnessed the power of cutting-edge deep learning architectures to extract advanced image features. Our toolkit included established models like VGG16 [10] and ResNet [6], alongside the latest in neural network architectures for visual feature extraction CLIP [9]. We analyzed the prediction power of features extracted from each architecture using three linear models as presented in Table 2. Notably, the deep learning feature extraction methods outperform individual visual features in predicting image attractiveness. This aligns with previous research, highlighting the superior performance of deep learning embeddings over low-level visual features within the context of food application [2, 12].

Table 2. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

	Image features extractor		
	VGG16	ResNet	ClipOpenAI
R^2	0.351***	0.349***	0.357***
RMSE	1.500	1.491	1.501

4.2 RQ2: User Characteristics and attractiveness

We examine the user factors on the image attractiveness. Accordingly, we split the user factors into different categories: User demographics, User profile, which represents the essential backbones of a food knowledge-based recommender system, and User knowledge, which measures the user's food knowledge and cooking skills. Confirmatory factor analysis shows that both subjective food knowledge and cooking skills adhered to internal consistency guidelines

($\alpha > .70$) while they also met guidelines for convergent validity based on the average variance explained (AVE > 0.5) as presented in Table 3.

Table 3. Results of the principal component factor analysis across different subjective food knowledge and cooking skills. Items were measured on 5-point Likert scales. Cronbach's Alpha is denoted by α.

Aspect	Item	Loading
Subjective Food Knowledge α = .86 AVE = .85	Compared with an average person, I know a lot about healthy eating.	.82
	I think I know enough about healthy eating to feel pretty confident when choosing a recipe.	.82
	I know a lot about how to evaluate the healthiness of a recipe.	.79
	I do not feel very knowledgeable about healthy eating.	-.90
Cooking skills α = .75 AVE= .53	I can confidently cook recipes with basic ingredients.	.74
	I can confidently follow all the steps of simple recipes.	.73
	I can confidently taste new foods.	.61
	I can confidently cook new foods and try new recipes.	.85
	I enjoy cooking food.	.66
	I am satisfied with my cooking skills.	.68

Table 4 presents the outcomes of the linear regression model aimed at forecasting the attractiveness of image recipes [F(9,2090)=3.60]. Remarkably, among the various user factors examined, only two demonstrated significant contributions to recipe attractiveness: cooking skills (β = 0.34, p-value= 0.00021) and recipe website usage (β = 0.18, p-value= 0.020). Intriguingly, none of the other user aspects significantly impacted user ratings for a given image recipe.

We inspected no variations in the impact of basic visual features and user factors on the attractiveness of images in the comprehensive linear model, encompassing all user and visual features, including all user and visual features. Consequently, basic visual features exert a more significant impact on food image attractiveness than user features, consistent with findings from previous research [11, 14].

4.3 RQ2: Food Image Dimensions, User Judgment and Image Attractiveness

To assess the influence of different food image dimensions on user ratings for food images, we developed a linear model [F(4,21) = 2.41] predicting image attractiveness based on food image dimensions. Appearance exhibited a significant impact on user ratings (β = 0.12, p-value= 0.03), indicating its higher significance. Additionally, the expected healthiness in the image also demonstrated a significant impact(β = 0.07, p-value= 0.03). However, perceived taste and familiarity did not show a discernible impact on user ratings.

To discern the impact of various image dimensions on user ratings for food images, we constructed a linear model [F(4,21) = 2,41] predicting image attractiveness using food image dimensions as presented in Table 5. Appearance, has a higher significant impact on the user ratings (β = 0.12, p-value= 0.03), in addition reflected healthiness through the image also shows a significant impact (β = 0.07, p-value= 0.03), while perceived taste and familiarly shows no impact on the user ratings.

To understand the textual assessments of food image attractiveness provided by respondents, we employed fundamental Natural Language Processing (NLP) techniques, including punctuation removal, handling repeated characters, and eliminating stopwords. Based on significant food image dimensions (e.g., Appearance, Healthiness 5), we analyzed 2109 judgments; we generated a word cloud highlighting the most prevalent terms related to appearance and healthiness,

Table 4. Linear regression models predicting user rating for recipe image attractiveness based on user factors. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

User Factors	$\beta(S.E)$
Constant	4.00 (0.57) ***
User Demographics	
Age	-.04 (.57)
Education	-.40 (.11)
Gender	-.07 (.08)
User Profile	
Recipe Website Usage	.18 (0.08)*
Home Cook	-.01 (0.08)
Cooking Experience	-.05 (0.07)
Eating Goals	.01 (0.06)
User Knowledge	
Subjective Food Knowledge	-.20 (0.13)
Cooking Skills	.34 (0.34) ***
R^2	0.015***
RMSE	1.845

Table 5. Linear regression model predicting user rating for recipe image attractiveness based on basic image features. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Food image dimensions	$\beta(S.E)$
Constant	3.48 (0.36) ***
Appearance	0.12 (0.06)*
Taste	-0.01 (0.05)
Healthiness	0.07 (0.03)*
Familiarity	0.02 (0.03)
R^2	0.011*
RMSE	1.855

offering an easy means to comprehend the reviews. Figure 1 shows the word spread for both attractive and unattractive respondent's judgment.

Additionally, based on food image dimensions, we randomly selected a few user textual judgments as presented in Table 6.

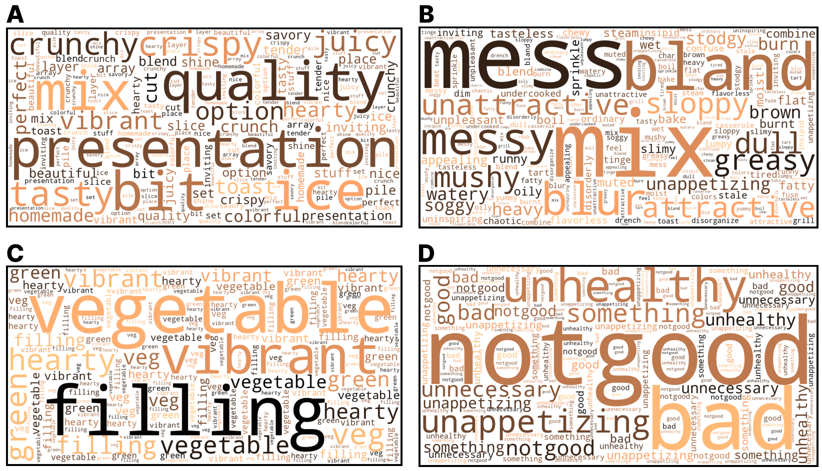

Fig. 1. Word cloud for terms in the user judgment: (**A**) : Attractive image judgments related to appearance, (**B**): Unattractive image judgements related to appearance., (**C**) : Attractive image judgments related to healthiness, (**D**): Unattractive image judgements related to healthiness.

Table 6. Results of the principal component factor analysis across different subjective food knowledge and cooking skills. Items were measured on 5-point Likert scales. Cronbach's Alpha is denoted by α.

Food Image Dimension	**Attractive Image Judgment**	**Unattractive Image Judgment**
Appearance	*- Can see the dish in its entirety and nice presentation.* *- The image quality, angles and placement of the food is perfect.* *- it looks sweet and crispy.*	*- It looks messy..* *- The image is blurry, the food looks bland.* *- It's hard to tell but looks a little mixed.*
Healthiness	*- Looks quite tasty and filling..* *- Looks healthy, pasta with vegetables look good.* *- the vibrant colours seem like they add a very good flavour to the salad.*	*- Chicken is unhealthy and gross.* *- Cheese is in no way healthy or good for you* *- Very unclear, terribly unappetizing and poor quality food.*

5 CONCLUSION AND FUTURE WORK

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