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Visual Attractiveness of Food Images: Exploring User Perception

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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

2.1 Contribution

The main contribution of this work is to gain insight and understand what influence user judgement of a food images.

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.

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3.1 Dataset

3.2 System Design and Procedure

3.3 Study Participants

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	0.11***
RMSE	1.75

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 [8] and ResNet [5], alongside the latest in neural network architectures for visual feature extraction CLIP [7]. 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 [1, 10].

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 used in previous work [2] and User knowledge that measures the user food knowledge and cooking skills, which were validated in previous studies [3, 4, 6]. 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 ($\beta = 0.34$, p-value= 0.00021) and recipe website usage ($\beta = 0.18$, 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 [9, 11].

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

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 [11] 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. Analyzing 2109 judgments, we generated a word cloud highlighting the most prevalent terms, offering an easy means to comprehend the reviews. Figure 1 shows the word spread for both attractive (1.A) and unattractive (1.B) images.

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

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

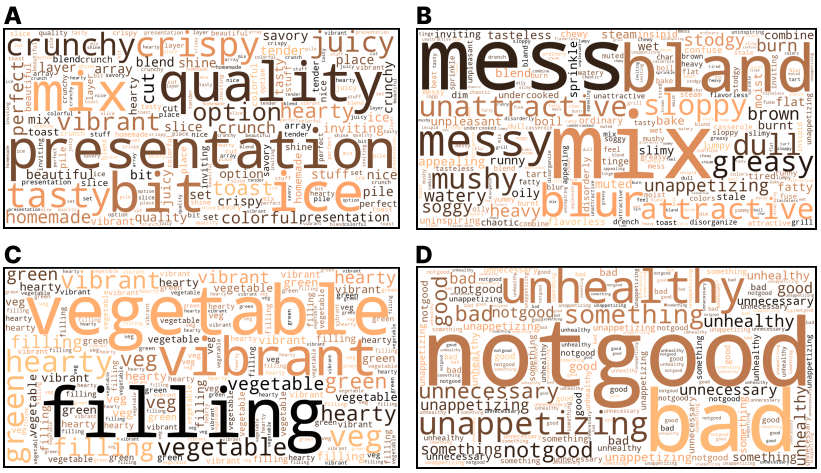

Fig. 1. Word cloud for terms in the user judgment: A: word in attractive images, B: word cloud for unattractive images.

5 CONCLUSION AND FUTURE WORK

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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	*- The colors on the plate are attractive. The presentation is perfect and the food looks healthy, and the meal looks balanced.* *- Well presented, the colors are complimenting. Simple but beautiful presentation.* *- High-quality photo, I can see all the details of the dish and what it contains. Influences me to want to make it myself.*	- Looks too dark and not yummy. *- Too greasy, doesn't look appetizing.* *- The colors of the food are plain and the food looks so bland.*
Taste	*- Food looks incredibly fresh and inviting, it looks like it would taste excellent.* *- Although I don't like olives this looks lovely and colourful and mediterranean. It looks like it has a lot of taste.* *- I would really like to taste that.*	*- The soup looks like it has no taste or extra tinge to it.* *- The salad looks so plain and lacking in both texture and in taste.* *- It only looks healthy because its vegetables but it does not look tasty at all.*
Healthiness	*- There is plenty of protein.* *- Looks healthy, wholesome and colourful.* *- Healthy ingredients that are all nicely chopped up.*	*- This looks very soggy and unhealthy.* *- Cheese is in no way healthy or good for you* *- Chicken is unhealthy and gross.*
Familiarity	*- Pasta is one of my favorite foods, and this one looks tasty because of how many tomatoes there are.* *- I love pumpkin pie.* *-I gave the max, because I love cheese and this one looks really good.*	*- I don't really like things such as chickpeas, plus it looks like there are tomatoes* *- I have never eaten Blackberry grunt.* *- The pasta looks revolting; it looks bland, like tasteless mush.*

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