Can AI Help Inspire Healthy Eating? Exploring the Potential of Generated Motivational Texts and Images Related to Healthy Food Choices

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ABSTRACT

A variety of open-source resources are currently available to potentially help inspire healthy eating, which is an important part of supporting one's overall well-being. We explored several ways in which one might harness web-driven and AI processes to find texts and images created by two approaches: traditional human authoring and generated by humans using support from AI models. We then recruited Mechanical Turk study participants to investigate how individuals would perceive these texts and images in the context of inspiring healthy eating.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

healthy eating inspiration, online food communities

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1 INTRODUCTION

A poor diet is considered one of the leading global risks to health [21]. In fact, unhealthy eating behaviors are part of the main preventable risk factors for chronic non-communicable diseases, which are the predominant cause of death globally [9]. Addressing the global increase in obesity and related diseases requires continuous, coordinated efforts employing a variety of prevention strategies across multiple levels [17].

Harnessing community-driven and web-driven computational methods alongside recent advances in artificial intelligence (AI) techniques may be one powerful means of addressing this issue and inspiring many people to pursue healthier eating behaviors. However, it is unclear whether AI-generated texts and images would be welcome or useful in inspiring online communities that support healthy eating.

To determine the answer to this question, we gathered a collection of human-authored and AI-generated texts and images that could potentially be perceived as inspirational for healthy eating. Traditionally human-authored content was gathered by scraping online websites via the Google and Pixabay search engines. Images were generated using stable diffusion, and texts were generated using the open-source GPT-J deep learning language model. We then recruited Mechanical Turk participants to judge these texts and images in terms of their potential for inspiring healthy eating. The overall contributions of this work include:

- Human-authored texts scraped from online sources and generated texts via the GPT-J deep learning model were found to be similarly inspirational for healthy eating (Study 1).
- Human-created stock photos scraped from online sources and photos generated using stable diffusion were both deemed by the majority as *delicious* and *healthy* (Study 2). A greater majority of individuals tended to rate the photos generated with stable diffusion (versus human-authored) as *healthy*. Likewise, a greater majority rated the human-created stock photos as *delicious*.

2 RELATED WORK

Advances in open-source AI techniques have led to an increase in AI-generated content and concerns about possible risks along with issues of trust, ethics, and accountability [31]. Accordingly, negative perceptions of AI-generated content have also been observed. Ragot et al., for example, recently demonstrated that humans display a negative bias for AI-generated art and a preference for artworks presented as made by humans without AI (2020). Similarly, when texts are generated by AI they are perceived as less trustworthy [12].

However, researchers have also suggested that AI-generated media can benefit individuals in particular contexts. As just a few examples, AI-generated music has been found to inspire creative activities [5], while generative AI models are currently being used to help reconstruct and fill in blank parts of scientific data (e.g., [4, 18]) or adapt to user needs in education [22]. Using AI-generated content to support healthcare is another area of rising interest. Prior work by Schmälzle and Wilcox has suggested that AI text generation might be used to promote statements for public awareness about health issues (2022). Others have attempted to use AI as conversational agents to address the high demand for healthcare services [13, 19]. Given these examples, it is reasonable to consider whether AI-generated content might similarly be able to promote and inspire healthy eating.

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To this end, we must first consider barriers to healthy eating and whether computer-supported cooperative work approaches might be appropriate. Related past work has certainly been used to support and investigate healthy eating (e.g., [6, 15, 23, 26]). Particular to the questions presented here, past research has shown that "healthy diets do not appear to be viewed as easy or attractive alternatives to current diets" and such perceived barriers in addition to a lack of knowledge are a persistent global issue [1, 2, 7, 11, 14, 28, 30]. At the same time, activities such as viewing digital meal photos perceived to be healthy and delicious in a community-driven app have shown promise for encouraging individuals to try new foods and eat healthier [10]. Research has further shown that motivational texts may potentially be effective in certain contexts [3] and there are various motivations for pursuing healthy eating behaviors. In particular, *autonomous motivation* stems from factors such as "congruence between the behavior and personally meaningful goals and values...and/or personal valuation of the outcome" and is associated with healthy eating success [16]. AI-generated content or other computational methods might thus be used as part of community-driven websites to help individuals identify personally-meaningful values and goals that are aligned with healthy eating behaviors, resulting in improved health outcomes overall. One benefit of such an approach could be that the generated content could be adaptive to the users' needs, although any such work must take issues related to user privacy and ethics into account [20, 29]. In this work, we consider the first step toward this objective by investigating whether human-authored and AI-generated texts and images might broadly be perceived as inspirational for healthy eating.

3 STUDY 1: JUDGING INSPIRATIONAL TEXTS FOR HEALTHY EATING COMMUNITIES

3.1 Research Questions

For Study 1, we were interested in the following research question (Research Question 1):

(1) Are texts that describe a reason for healthy eating judged as similarly inspirational for healthy eating if they are (a) generated by humans with the GPT-J deep learning language model versus (b) scraped from online human-authored blogs?

We note that human-authored texts scraped from online blogs do not necessarily represent human-authored text content as a whole. The point of this study is thus not exactly to compare "AI-generated" texts with "human-generated" texts, but instead to provide an initial understanding of how these two computer-supported techniques might influence human judgements, and whether there is any preliminary evidence that either technique might inspire healthy eating.

Given the current negative sentiment against AI-generated media and possible issues due to incomplete AI comprehension (especially with a lower-performing model like GPT-J), we hypothesized that individuals would not rate the generated texts as inspirational for healthy eating as often as the fully human-authored texts scraped from online sources.

3.2 Method

We first gathered 36 sentences about being inspired to pursue healthy eating. 18 of these sentences were generated using GPT-J (6B), an open-source and 6-billion parameter transformer model released by the Eleuther AI group. Sentences were generated by providing the model with prompts such as "I'm inspired to eat healthier because", "I'm inspired to eat healthy because", and "I'm motivated to eat healthy food because" (six sentences per prompt for an even split). In each case, only the first sentence was used for the purposes of this study, even if more text was generated after the first sentence. The remaining 18 text statements were scraped from online blogs using the Google search engine with the same prompts, using the first 18 results retrieved (evenly split among prompts). Again, only the sentence found that was directly related to the prompt was used and no further statements were retained in each case.

We recruited 60 participants from Amazon Mechanical Turk to participate in Study 1, which was approved by the Institutional Review Board at the author's institution. All participants were informed that the academic researchers leading this study were conducting a survey about how people judge texts and images in terms of their inspirational potential for healthy eating, and that their participation was voluntary. Participants were compensated $3 for their time and completed the survey questions (for both Study 1 and Study 2) in less than 12 minutes.

After accepting the terms and choosing to start the task, all participants were asked to consider each of the 36 texts in turn, and judge whether the text helps inspire healthy eating. This was a binary choice: they could either select a text was *inspirational*, or *NOT inspirational*. We then compared the results for the GPT-J texts versus the blog texts to address Research Question 1.

3.3 Results

Across all participants, the texts were labeled as inspirational approximately 83% and 78% of the time for the deep learning generated and scraped blog post sentences, respectively. The median percentage deemed inspirational for each group was approximately 65% (Blog) and 61% (GPT-J). A two-tailed paired t-test further indicated that the difference between the percentages of these two groups for each text was not statistically significant (Research Question 1, refer to Table 1).

Condition	n	Mean (μ)	StDev (σ)	t	p
Blog	18	62.228	15.180	0.1371	0.893
GPT-J	18	61.572	16.153		

Table 1: Results of a two-tailed paired t-test when comparing texts scraped from blogs and texts generated by GPT-J in terms of their perceived potential for inspiring healthy eating (Study 1, Research Question 1). By conventional criteria, the difference was not considered to be statistically significant.

4 STUDY 2: JUDGING INSPIRATIONAL MEAL PHOTOS FOR HEALTHY EATING COMMUNITIES

4.1 Research Question

In Study 2, we were interested in how individuals would judge food images in terms of the following attributes: creative, delicious, healthy, inspirational, and pretty. In particular, we were interested in images as generated by (1) humans using a stable diffusion process to generate photos [25] versus (2) humans using web scraping retrieval of stock photos (which were verified as human-authored). Our research question (Research Question 2) was as follows:

(2) Are food images tagged as delicious and healthy judged similarly in terms of qualities such as *creative*, *delicious*, *healthy*, *inspirational*, and *pretty* if they are (a) generated by humans with stable diffusion versus (b) scraped from human-authored stock photos using the same prompts?

Again, we note that both techniques are human and computer-supported (although one particularly uses stable diffusion rather than relying on human-authored photographs), and that the human-authored photos retrieved are not necessarily a representation of all human photographs. This study represents an exploration of how each technique may, if at all, influence human judgements. Similar to Study 1, we hypothesized that individuals may express a hesitation or disappointment with the AI-generated images versus the human-authored images.

4.2 Method

We asked the same 60 participants from Study 1 to participate in Study 2, which was also approved by the Institutional Review Board at the author's institution. Participants were provided with five pairs of comparable food photos. Each pair of images contained one image generated by stable diffusion via the prompt "a delicious healthy *variable*", where *variable* was replaced by one of five categories of food (*appetizer*, *dessert*, *drink*, *sandwich*, and *soup*). The remaining image in the pair was obtained by retrieving stock photos submitted by humans to the Pixabay website by using the same corresponding prompt. In each case, no cherry-picking was allowed; that is, the first image that was retrieved based on the prompt was selected for the study. To provide an idea of what participants viewed in this study, a pair of images generated by stable diffusion versus taken by a human (in this case, a freely-available photo rather than a stock image) is displayed as an example in Figure 1. Once participants viewed the study details and chose to begin Study 2, they were asked to consider the ten photos in turn and indicate whether each was (1) creative, (2) delicious, (3) healthy, (4) inspirational, and (5) pretty. This was done through five checkboxes for each image; thus, a photo could be rated with up to all five of the attributes.

4.3 Results

On average, the majority of participants tended to rate images in both groups as *delicious* and *healthy*. No statistical significance between the two groups of images was observed when considering judgements for the *creative*, *inspirational*, and *pretty* categories.

A difference in two proportions hypothesis test suggested a statistically significant difference for the *healthy* category (z=1.96 for stable diffusion vs. stock photo). The mean percentage of individuals who rated the images as healthy was approximately 75.2% and 56.3% for the stable diffusion and stock photo groups, respectively. Using the same test, the opposite was reached for the *delicious* category (z=-1.96 for stable diffusion vs. stock photo). The mean percentage of individuals who rated the images as delicious was approximately 53.0% and 71.3% for the stable diffusion and stock photo groups, respectively.

(a) AI-generated with stable diffusion

(b) Human-authored (non-stock)

Figure 1: Examples of freely-available photos one might retrieve through stable diffusion [25] or Pixabay [8] with the prompt *a delicious healthy pizza*.

5 DISCUSSION

Results from Study 1 indicate a promising future for finding and generating text statements to help inspire healthy eating. In Study 2, it is understandable that the majority of participants in both conditions tended to rate the images as both delicious and healthy given that these two adjectives were part of our image collection prompts. However, it was surprising that a AI-generated photo would more often be deemed as healthy and the human-authored stock photo more often categorized as delicious. Future work should repeat this experiment with a larger dataset of images and should seek to discover the reason for this discrepancy if the same pattern holds. It is possible that, when creating stock food photos, humans are typically focused on (for example) whether the food appears delicious to many individuals as opposed to whether it appears to be healthy, even though the retrieved photos were found via a search for specifically healthy and delicious food. Future work might also explore whether a similar vetting process as seen in Study 1 might be useful when selecting images with beneficial characteristics that inspire healthy eating.

Given that there were not many results from online sources when using the text prompts in this study, future work could examine new approaches for gathering inspirational statements from online sources related to healthy eating. We also suggest that any such algorithms for public use identify the source and credit the individual(s) who made the statement. Even if it is not easy to find human-authored inspirational texts (and sometimes specific images) in this regard, a human might also generate more possibilities using a deep learning model like GPT-J. We suggest that research going forward also build upon the vetting approaches presented in this study and determine how to customize suggested inspiration for users (e.g., find the kind of text that motivates you specifically and in your current context).

6 LESSONS LEARNED AND FUTURE DIRECTIONS

Our results suggest the following key lessons learned:

(1) **Traditional human-authored texts and AI-generated texts can be inspirational for healthy eating.** In both conditions, participants rated gathered texts as inspirational approximately 80% of the time. Future work might characterize and seek to expand the degree of usefulness of these kinds of texts further. For example, how might new inspirational texts for healthy eating be gathered that continue to be novel and inspirational for the same individual over the long term?

(2) **Traditional human-authored and AI-generated photos gathered by querying for *delicious* and *healthy* food appear to often result in being judged as *delicious* and *healthy* by the majority of individuals.** Future work might examine a greater variety of food photos to ensure that this pattern holds. More specificity in the prompt may make the comparison between techniques more "fair" (e.g. specific: *chicken avocado sandwich* vs. more generic: *sandwich*), as long as there are available photos for such a level of specificity. Additionally, future work might explore different kinds of techniques for creating or generating these kinds of photos, as well as related domains.

Overall, these studies suggest that there are several means of gathering texts and images that are perceived as beneficial for inspiring healthy eating. Future research might explore how techniques such as these might be leveraged to further support individuals in online community-driven spaces as they seek to pursue healthy eating lifestyles.

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