Appealing to the Gut Feeling: How Intermittent Fasters Choose Information Tab Interfaces for Information Acquisition

Hyeyoung Ryu\textsuperscript{1,2} and Seoyeon Hong\textsuperscript{2}

\textsuperscript{1} University of Washington, Seattle, WA 98195, USA
hyryu115@uw.edu
\textsuperscript{2} Yonsei University, Seoul 03722, Korea
seoyeonhong@yonsei.ac.kr

Abstract. Although many deem intermittent fasting (IF) a healthy dietary regimen, there is a paucity of scientific evidence to corroborate IF health benefits in human studies. However, its comparative ease and the emphasized benefits in the light of COVID-19 (e.g., weight loss and immunization improvement) have led to the increase of IF adoption. A vast number of intermittent fasters have not sought consultation from health professionals, which can bring adverse health effects. Most intermittent fasters use mobile apps to get assistance for IF. Types of assistance offered by the IF mobile applications may range from tracking (e.g., fasting periods, calorie intake) to obtaining knowledge about IF. However, it is unclear how much people are using the features for learning more about IF which is crucial to making healthier decisions in the IF adoption process. Thus, we organized our study into two stages for establishing design implications that further encourage a safety-conscious and user-friendly IF experience. We first investigated how IF app users who have chosen apps that provide extensive IF-specific knowledge acquire the said knowledge via (i) topic modeling of user app reviews, (ii) detecting modularity in co-word maps drawn from reviews specific to IF information acquisition, (iii) locating the position of keywords indicating information acquisition in the reviews. Then, we examined how users judge the effectiveness of knowledge provision interfaces in obtaining information. We investigated this aspect with an interface ranking user task for information tabs and organized user rationale using manual coding and co-word mapping.

**Keywords:** Intermittent fasting · Safety-conscious diet · Text mining · Mobile application · Information acquisition

1 Introduction

Alaine, a hypothetical 2-week intermittent faster, is amazed by her weight loss. She notes in her review of the app, “I can eat anything as long as it’s within my

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8 h eating window. Just need to check track the time with my intermittent fasting tracker app.” This is a common approach taken by the increasing adopters of the intermittent fasting (IF) lifestyle. There are various forms of IF but they share the foundation that the benefits of IF are derived from taking periodic breaks from eating [43]. The most common forms of IF are time-restricted feeding where intermittent fasters would limit the eating window to 8 hs and fasting for 16 h [48] or periodic prolonged fasting in which calorie intake would be limited or restricted on the 2 weekly fasting days [41]. Although IF is perceived as a healthy dietary regimen [26], the paucity of scientific evidence to corroborate the health benefits in human studies [9,17] as opposed to the more concrete animal trial studies [1,7,43] which indicates that there is a lack of evidence for recommending IF for public health practice [33]. However, its overemphasized benefits (e.g., weight loss [9,26] and immunization benefit in the light of COVID-19 [16,49] over surfacing health downsides such as loss of lean muscle mass [24] has led to its surge of adoption [33]. It is also a rising concern that many of those who have incorporated IF into their lifestyles have not sought consultation from health professionals, which can lead to adverse health effects, especially in the case of those with medical conditions more affected by dietary intakes such as diabetes [31]. In many dietary change applications, the focus has been on motivation for a longer commitment to the diet in diverse forms: peer support [29,36], rewards and punishments [32,47], and goal tracking [25,42]. However, since the long-term benefits of IF have not been fully proven with human trials, precautionary measures of informing the users of IF related knowledge should be taken to a greater degree before encouraging the partially credible benefits. The precautionary measures can be implemented most widely with mobile applications for IF as the IF app market is expanding [23,34,45,46] and gaining popularity among users [21,39]. In the IF mobile applications, the types of assistance may range from time and calorie tracking to gaining knowledge about IF. With only partially confirmed benefits of IF, the usage of the last type of assistance needs to be investigated for a safety-conscious and healthy dietary change through IF. Thus, we investigated two aspects of IF-related knowledge acquisition from applications for establishing design implications of a more safety-conscious and user-friendly IF experience. The first aspect is if and how people who have chosen applications with extensive IF-related knowledge acquire the said knowledge via (i) topic modeling of all user reviews, (ii) modularity detection in co-word maps specifically for IF related information acquisition reviews, and (iii) index location of the words indicating information acquisition in the reviews. The second aspect is how users judge which knowledge provision interface is more effective for information acquisition with comparison of the five types of interfaces. We investigated this aspect with an IF application information tab interface ranking task and both manual coding and co-word mapping of the rationales users provided for their ranking process.
2  Related Work

2.1  Lacking Robustness of Human Studies on Intermittent Fasting Health Benefits

The popularity of IF has increased for its claimed benefit on health, such as weight loss and immunization benefits. Patterson and Sears [33] stated that the October 2016 search result for “diet fasting intermittent alternate day” had more than 210,000 hits. Four years later, the October 2020 search result for the same query had approximately 2,110,000 results. Amid COVID-19, people have reported weight gains and sought ways to lose weight [2, 49] and increase their immunization to lower their chances of contracting COVID-19 [16]. Thus, the advantages of IF are appealing to the vast majority. However, the advantages of IF are not yet proven with certainty in human clinical trials although they have been proved through animal trials. Mattson and Wan [26] state that progressive increase in lifespan for rats through progressive decrease in calorie intake has been proven but they emphasize that there are no well-controlled human studies to corroborate the same health benefits for humans. Horne et al. [17] also support the need for further research with humans to build stronger grounds for the benefits of IF than the status quo, especially for metabolic health and cognitive performance improvement, and long-term cardiovascular outcomes.

Moreover, Stockman et al. [43] state current IF research lacks robustness as the individuals who would benefit the most from IF is still unclear and deters healthcare professionals from recommending IF to patients as standard practice. Lowe et al. [24] even points out that lean muscle mass may be a side effect of IF but there are even caveats to this study in that it had a relatively small sample size and only looked at the metabolic effects of IF. Therefore, intermittent fasters need to be better informed of the evidence-based support of IF mechanisms and its benefits and harms to adopt a form of IF that would possibly benefit them the most [33].

2.2  Text Mining User App Reviews

Because mobile app reviews carry a plethora of information on user experience and expectations [13], we collected user reviews of current IF apps to evaluate the practices of information acquisition of IF app users. Previous research implemented LDA topic modeling to organize user reviews into coherent topic clusters for identifying app features [8, 11, 12, 27, 35]. Sullivan et al. [44] conducted LDA topic modeling on Amazon product reviews to distinguish potentially unsafe nutritional supplements by searching for topics insinuating adverse reactions. Topic modeling is often paired with sentiment analysis for user opinion mining [10, 14, 15, 22]. Guzman and Maalej [15] proposed a framework for analyzing user reviews by using App Store reviews to extract app features through LDA and then using sentiment analysis to determine user satisfaction level of each feature. Guo et al. [14] performed sentiment analysis on topics to discover key dimensions for improving hotel management. Lin and He [22] proposed a joint
sentiment/topic model (JST) that simultaneously identifies sentiment and topic. Diao et al. [10] devised a recommendation system trained by integrating topic modeling, movie ratings, and sentiment analysis using movie reviews. Therefore, building on previous literature, we proceed with LDA topic modeling and sentiment analysis to determine the current status of information reception among IF app users.

3 Information Reception of IF App Users

3.1 Data Collection

We scraped 34,886 app reviews from Google Playstore and 15,082 reviews from Apple Appstore until September 2020 from the following five current apps that provided a separate learning section: (a) Life Fasting Tracker, (b) Simple: Fasting & Meal Tracker, (c) BodyFast Intermittent Fasting Tracker - Diet Coach, (d) DoFasting - Intermittent Fasting & Healthy Diet, and (e) MyFast - Intermittent Fasting Tracker Schedule App. From the collection, we eliminated the 11,730 reviews with insufficient length (i.e., 50 characters and below), which do not suggest significant meaning (e.g., “Love it Sooo good”) from analysis to optimize topic model performance.

3.2 Data Preprocessing

The LDA model requires a dictionary and a corpus. A dictionary assigns a unique ID to each token in the entire document collection, while a corpus produces a mapping of each document referencing the dictionary [5]. Before tokenizing our data, we proceeded with data cleaning using NLTK [4]: (a) we removed English stopwords (i.e., frequently used words that do not convey much significant meaning that discourages optimal model performance), (b) extracted nouns and verbs from the text using Part-of-Speech tagging, (c) then lemmatized the words to restore inflectional word forms to its base form [4].

3.3 Topic Modeling

To determine the elements of IF apps most valuable to users, we employed topic modeling to discover abstract topics within app reviews. Latent Dirichlet Allocation (LDA) is one of the most frequently used topic modeling methods [19]. LDA is an unsupervised learning algorithm that assumes that each document was generated by assembling a mix of topics, then selecting the words that belong to each topic [5]. Python packages such as Gensim [38] and Mallet [28] allow LDA implementations. To optimize model performance, we compared the performances of different models trained on (a) nouns, (b) verbs, (c) nouns and verbs, in unigram and bigram forms using Gensim and Mallet. To find the optimal topic number, we used the elbow method, sampling a range of 2 to 50 to discover the model that yields the best coherence value as it shows the most accurate way to determine the number of topics for the model [30].
3.4 Sentiment Analysis

From the topic modeling result, we proceeded to investigate the users’ sentiment on each topic via sentiment analysis \[40\]. Using VADER (Valence Aware Dictionary and Sentiment Reasoner), the lexicon and rule-based sentiment analyzer \[18\], we evaluated each review’s sentiment and extracted the dominant sentiment and its distribution for each topic. We used compound scores to classify sentiments, which provide a normalized score between \(-1\) and \(1\), calculated by adjusting the sum of each word’s valence in a document.

3.5 Results

Our LDA model generated 41 topics with a coherence score of 0.4637 (see Fig. 1), built using Mallet, and trained on noun unigrams. From those 41 topics, we reassembled highly correlated topics (e.g., topics such as “Weight Loss” and “Body Slimming”) and excluded topics that only pertained to app performance or payment (e.g., “Working now: was glitching but the issue was resolved!”), or were shallow comments regarding the app (e.g., “I just love using this app, and have not had any issues this far. It’s great!”).

![Coherence value per number of topics used in LDA topic modeling](image)

**Fig. 1.** Coherence value per number of topics used in LDA topic modeling

Table 1 summarizes the organized result, which consists of 18 topics and its dominant sentiment, classified into five main categories: (a) tracking features, (b) informational features, (c) user intent, (d) usability, and (e) user interface.
User reviews pertaining to the use of IF information tab (i.e., topic 9) constituted only 2.23% of all reviews, implying that users are less prone to active acquisition of IF-related knowledge, compared to other informational features which users are involuntarily exposed to (i.e., guided schedule, workout routines, meal recommendations form 15.83% of all reviews). Furthermore, the IF-specific informational features were one of the most highly rated by users among app features besides calorie tracking, with 96% of its reviews being positive, which begs further inspection on design implications for effective information acquisition.

Table 1. Intermittent fasting app review topics and dominant sentiments

| Category            | Topic                                                                 | Percentage | Sentiment   |
|---------------------|-----------------------------------------------------------------------|------------|-------------|
| Tracking Features   | 1 cal Tracking                                                        | 9.34%      | Positive (96%) |
|                     | 2 The Range of Tracking Features Provided                             | 6.99%      | Positive (93%) |
|                     | 3 Food Intake Tracking & Dietary Guides                               | 2.68%      | Positive (92%) |
|                     | 4 Time Logging                                                        | 2.50%      | Positive (84%) |
|                     | 5 Notifications & Reminders                                           | 2.09%      | Positive (89%) |
| Informational Features | 6 Guided Schedule                                                   | 6.64%      | Positive (87%) |
|                     | 7 Workout Routines                                                    | 4.77%      | Positive (94%) |
|                     | 8 Meal Recommendations                                                | 4.42%      | Positive (89%) |
|                     | 9 Information Tab Evaluation                                         | 2.23%      | Positive (96%) |
|                     | 10 Quality of Paid Content (Subscription)                            | 2.22%      | Positive (47%) |
| User Intent         | 11 Accounts of Weight Loss                                           | 15.62%     | Positive (91%) |
|                     | 12 Changing Lifestyle & Increasing Fitness                           | 3.45%      | Positive (92%) |
|                     | 13 Improving Health                                                  | 2.53%      | Positive (91%) |
| Usability           | 14 Ease of Use                                                       | 5.32%      | Positive (94%) |
|                     | 15 Does not Accommodate Different Lifestyles (e.g. night shift)       | 3.24%      | Positive (87%) |
|                     | 16 Customization                                                      | 1.63%      | Positive (90%) |
| UI                  | 17 User Interface Judging Criteria (e.g. intuitiveness, simplicity, user-friendliness) | 3.73%      | Positive (96%) |
|                     | 18 App Aesthetics (e.g. “love the arc and icons”, “I like the different ways to see my stats”) | 1.82%      | Positive (88%) |

To investigate the informational features section further on how each word related to knowledge was associated with other topic-representing nouns and sentiment-reflecting adjectives, we calculated the co-occurrences of the reviews with informational features and clustered the co-occurrences using the Louvain algorithm [6] for modularity detection to create the co-word map on Gephi (an open source software network analysis program) [3]. We used co-word maps as it is more accurate in detecting topics than topic modeling when there are less than 1,000 inputs [20]. The node sizes and labels are shown to be ranked by each node’s betweenness centrality score which implies the nodes’ extent to which a
vertex lies on paths between other vertices to determine the central nodes [37]. Nodes that lie on the shortest paths will have higher betweenness centrality, and as shown in the co-word map, words indicating relations to knowledge are represented as having a prominently larger size node and node label as they would be used as the keywords of the sentences (e.g. tip and information).

We found that words with high betweenness centrality (higher than 0.5 in normalized betweenness centrality scores) relevant to information acquisition in the co-word map was tip, guidance, information, article and knowledge (see Fig. 2). We observed that tip and guidance were used together frequently and that the related topics were exercise and recipes as well as motivation (e.g., “This one offers me daily motivation boosts, guidance, and useful tips”). The word information was associated with weight loss and nutrition, and related adjectives such as plenty, lot, and ton which indicated a vast amount of information (e.g., “Helps you track your food intake and its database on nutrition information is great”). The word article was highly associated with positive adjectives such as great and good which reflected users’ sanguine response to provided articles (e.g., “It has great, short, informational articles about fasting in general”). The word knowledge was associated with fitness and health (e.g., “...knowledge regarding overall body health, fitness and rapid weight loss”). The word question was associated with calorie and meal tracking during IF (e.g., “They provide personalized meal plans based on a set of questions you answer”).

As co-word maps do not show the position of information gain (IG) words, we calculated the position of the IG words by dividing the position of the word in the sentence by the number of words in the sentence and drew a density plot of the position of the IG words (see Fig. 3). We observed that the average of the IG word positions are mostly higher than 0.6. The skewness of the positions are all negative which means that most words are placed later in the sentence than the average. After observing all the sentences with positions higher than the average, we saw that the sentences were located at a later part of the sentence because they were mentioned as an additional part of the review (e.g. “also a lot of information about nutrition is given.”, “and articles are great.”). This reflects the perception of the knowledge provision sections as an auxiliary features from users who have tried out or are using said features.

4 Information Tab Interface Online Ranking Session

4.1 Procedure

In this session, we recruited 80 participants (46 female, 34 male) who have been using IF apps for more than three months. Participants’ ages ranged from 19 to 69 years (M = 31.77, SD = 12.68) We excluded one participant as she gave up on ranking the information tabs in the middle of the session. 27 participants had previously used the information tabs before and 52 had not. After asking them about their usage of information tabs, we asked them to watch 15 to 20s usage videos of the information tabs (i.e. scrolling through IF information categories, clicking and reading the subsidiary questions or articles) of the five
Fig. 2. Co-word map of topics in IF mobile application with information tabs reviews

Fig. 3. Density plot of position of information gain words
applications that currently have information tabs. Then, we asked them to rank the information tabs in order of effectiveness of information acquisition and provide rationale for the ranking. We investigated the reasons for why each group, one group that had previously used information tabs and one group that did not, ranked the interfaces in the way they did through co-word map creation of the reviews and the manual coding of the rationale text for themes.

4.2 Results

When we averaged the reverse rank (6 - actual rank) each of the information tab interfaces received from the participants, we saw that the BodyFast information tab interface had the highest reverse rank average, which meant that they were ranked the highest on average (see Table 2. On the contrary, Simple had received the lowest reverse rank average, which meant that they were ranked the lowest on average. Since the order of information tab interface was the same for both the group that used information tabs before and the group that did not, we probed the reasons why this ranking order was shared by both groups via co-word mapping (see Fig. 4) and manual coding of the rationales.

| Information Tab Usage | BodyFast | DoFasting | Life | MyFast | Simple |
|-----------------------|----------|-----------|------|--------|--------|
| Yes                   | 3.444    | 3.370     | 3.185| 2.704  | 2.296  |
| No                    | 3.635    | 2.981     | 2.962| 2.923  | 2.500  |

Although some participants have stated that their rationale for ranking was their gut feeling, some participants provided deeper insights to the “gut feeling”. The three specific themes for the ranking rationales were (i) information quality, (ii) information relevance, and (iii) information presentation. First, participants deemed the information quality to be higher or useful when the provided information was new or general. Second, participants felt that the information was relevant when the research articles provided were directly related to IF. Third, for information presentation, users said that having too many options to choose from discouraged their usage (i.e. “an overwhelming number of menus” and “Reducing the options is a must. It’s just too much.”). Also, participants said that the blurb of information (i.e. short and definitive answers) was better for them to obtain IF related knowledge. Moreover, the clutter of images and text discouraged participants from using the information tab.
5 Conclusion

With our three pivotal findings on the knowledge conveyance of IF applications, we have demonstrated (i) the lack of usage of the information tabs which represent voluntary information acquisition, (ii) how people use the information tabs and evaluate each usage, and (iii) the criteria IF application users use to rank learning effectiveness of IF information tabs. The three key takeaways for improving information acquisition from dietary change assistance applications, especially in cases like IF in which certainty of the outweighing benefits cannot be substantiated are the following:

1. Voluntary information acquisition from current IF applications with information tabs is low and regarded as an additional feature, although the information tab users deem the information acquisition experience to be positive.
2. Current knowledge acquiring users of the IF applications use the information tab for information gaining on exercising, recipes, health, meal and calorie tracking during IF.
3. IF application users evaluate the knowledge acquisition effectiveness of the information tab by information quality, information relevance, and information presentation.

If the three findings are incorporated into the future development of IF application information tabs, users like Alaine will be able to enjoy the benefits of IF with increased safety and user-friendliness in information acquisition.
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