Beyond calories: evaluating how tailored communication reduces emotional load in diet-coaching

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Abstract

Dieting is a behaviour change task that is difficult for many people to conduct successfully. This is due to many factors, including stress and cost. Mobile applications offer an alternative to traditional coaching. However, previous work on apps evaluation only focused on dietary outcomes, ignoring users’ emotional state despite its influence on eating habits. In this work, we introduce a novel evaluation of the effects that tailored communication can have on the emotional load of dieting. We implement this by augmenting a traditional diet-app with affective NLG, text-tailoring and persuasive communication techniques. We then run a short 2-weeks experiment and check dietary outcomes, user feedback of produced text and, most importantly, its impact on emotional state, through PANAS questionnaire. Results show that tailored communication significantly improved users’ emotional state, compared to an app-only control group.

1 Introduction

An unhealthy diet poses a serious threat to an individual’s health. Research showed that a poor diet kills more people than smoking (Afshin et al., 2019) and that obesity has tripled since 1975.1 Coaching through human experts is one of the most effective ways to improve diet (Gordon et al., 2017; Schmittdiel et al., 2017), but it can be too expensive for disadvantaged groups, adding to other costs associated with a healthy diet (Aggarwal et al., 2011; Barosh et al., 2014; Morris et al., 2014; Håkansson, 2015).

E-health apps are a cheaper alternative, although there is mixed evidence about their effectiveness (Wang et al., 2016; McCarroll et al., 2017; Lee et al., 2018; Aromatario et al., 2019).

Compared to experts, apps often show sub-optimal communication. Typically apps focus on data presentation (e.g.: charts), limiting the use of text to short and fixed messages. This could be the reason why previous apps evaluation focused primarily on diet outcomes. There has been little work on effective communication for dieting tools: this should be addressed as it plays a big role in engagement and adherence (Lee and Cho, 2017). Dieting habits are also known to be influenced by emotional state (Macht and Simons, 2011; Koenders and van Strien, 2011; Klump et al., 2016), yet no prior work on diet-apps investigated communication’s role in this.

In this paper, we implement an advanced communication strategy and investigate its effect on emotional state in the context of diet coaching apps. We exploit affective-NLG, text-tailoring and persuasive communication techniques to create weekly diet reports. Reports are implemented as an additional layer on top of a standard diet app, augmenting its communicative capability. We then proceed to evaluate our system in a short experiment. We compare participants that used the report-augmented app, with an app-only control group. Unlike previous work, we do not focus our human evaluation on dietary outcome only. We inspect communication adequacy through user feedback on a variety of measures including readability and accuracy. As a novel contribution we evaluate if our reports improved participant’s affective state. We adopt a validated psychometric tool, the PANAS questionnaire (Watson et al., 1988), to analyse the behaviour of both groups on a weekly basis. Participants who received our report experienced significantly more positive emotions and fewer negative ones. We also observe the opposite behaviour in the control group.

In Section 2 we expose the common limits of diet apps under the functional, communication and psychological aspect. We also briefly describe SOTA

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1https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight
Hello Dan18777, you told us that you want to gain some weight, so we wrote this report especially for you.

Your calorie intake could use some improvement: there was an occasional lack of food (generally you ate about a third less than your target). It was a bit better the previous time, we’re sure you can do it again!

Friday looks like the most problematic day (you ate about half of your target).

It seems that sodium and protein intake needs a bit of improvement.

Your sodium consumption was about half of your target. Of the foods you ate, “Spinacina” was the highest in sodium. It would be better to correct this as sodium deficiency can lead to cramps.

Also, your protein consumption was about half of your target. Last week it was better and we know you can do it again! “Pizza” was the food you ate which had the most protein. Keep in mind that protein deficiency can be responsible for muscle loss.

Figure 2: Example of a generated weekly report on the second week.

in communication-based systems for diet-coaching. In Section 3 we detail our approach to augmenting diet-coaching apps communication, and describe the implemented features. We present our experiment methodology in Section 4, and discuss the results in Section 5. In Section 6 we sum up our conclusions and present our future research directions. Finally, in Section 7 we detail the procedure through which we ensured ethical compliance for our experiment.

2 Related work

Today people can access lots of diet tools, but both academic and commercial products show some common limits. Some of these are purely functional: missing features that negatively impact on effectiveness. This includes low accuracy (Vasiloglou et al., 2020), fixed suggestions (Liefers et al., 2018) or the excessive use of humans in the loop (Teeriniemi et al., 2018). Low accuracy is an obvious limit to the app’s effectiveness; fixed suggestions overlook customisation and potential dangers (like allergies, user taste and religious food dogmas); major use of human experts nullifies apps’ usefulness in the first place. However, these problems can be solved by expanding the tool-set of features and evaluating dietary outcomes.

But if we consider the behavioural component of dieting, we raise different problems, for example at communication and psychological level. Previous research showed that behaviour change benefits more from advanced communication (Van Dorsten and Lindley, 2008; Balloccu et al., 2021; Whitehead and Parkin, 2022) than from factual text. Diet apps (Corcoran, 2014; Evans, 2017; Tredrea et al., 2017), however, do not follow this logic and favour data presentation, through visual features (like charts, color codes and tables) (Eikey, 2021). At communication level, used text is typically short, fixed and lacks informativeness (Vasiloglou et al., 2020).

Figure 1: Execution flow, from user subscription to report delivery.
A first way to improve the communication of diet apps could be the use of fine-tuned, domain-specific NLG, combined with text-tailoring (Kreuter and Wray, 2003; Noar et al., 2007) and persuasive communication (Guerini et al., 2011; Duerr and Gloor, 2021; Shabir et al., 2022). This is motivated by the relationship between personalisation and engagement in diet apps (Lieffers et al., 2018; Zmora and Elinav, 2021), and the role of persuasion in behaviour change (Orji and Moffatt, 2018; Balloccu et al., 2021). Additionally, NLG has been used in various healthcare domains (Reiter et al., 2003; Finley et al., 2018; Pauws et al., 2019; Hommes et al., 2019), including some work in nutrition. Shed (Lim-Cheng et al., 2014) is a tailored diet-system that exploits NLG to propose alternative meal plans in real time. Initial inspection of user acceptance showed it as a promising system for further evaluation. A conceptual diet-recommender system has been proposed (Ritschel et al., 2019), focusing on reinforcement learning for linguistic personalisation. Other work (Donadello et al., 2019) presented a NLG-based persuasive reasoner to address dietary guidelines violations. Evaluation showed the appropriateness of presented feedback, and its effectiveness in reducing the amount of violations compared to canned text. MADi-Man (Anselma et al., 2018; Anselma and Mazzei, 2020) is a persuasive diet-coaching system, developed to convince the user to opt for an healthier diet. Evaluation in both controlled and uncontrolled scenario revealed that users appreciated the presence of both visualisations and text, and confirmed its persuasiveness. While these works evaluated the use of persuasion and dietary outcomes, we note that tailoring involved only data analysis (e.g.: custom meal plans) and not textual features. Moreover, previous research did not inspect whether the adopted communication techniques had an effect on users’ emotional state. This aligns with previous evidence that diet-apps rarely consider this element (Ferrara et al., 2019). We know from nutrition research (Torres and Nowson, 2007; Puddephatt et al., 2020; Riffer et al., 2019) that user’s emotional/affective state influences eating habits, causing various issues including calorie excess (Fong et al., 2019), emotional (Macht and Simons, 2011; Van Strien et al., 2012) and binge (Klump et al., 2016) eating. The importance of this factor is also confirmed by previous research of the matter in other domains such as Cognitive Behaviour Therapy (Fitzpatrick et al., 2017), mental well-being (Ly et al., 2017), substance abuse (Prochaska et al., 2021) or emotional support in public speaking (Murali et al., 2021). To the best of our knowledge, this is the first work in NLG for nutrition that investigates the influence of the system on affective state.

3 Augmenting diet apps communication

We implement an NLG report generator for diet-coaching based on our previous work (Balloccu et al., 2020a)\(^4\), and use it to augment the communication strategy of a traditional diet app. We use MyFitnessPal (MFP) (Evans, 2017) as data source. The execution flow can be seen in Figure 1. The report is tailored based on various preferences. Users were asked to specify:

1. A nickname
2. Their motivation for using the system (e.g.: "I want to lose weight")
3. How they wanted to display quantities in reports. The options were pure values (e.g.: "50% of your calorie goal") or fuzzy quantification (e.g.: "half of your calorie goal")
4. Metrics of interest (one or more from: calories, carbohydrates, protein, fat, sodium and sugar)
5. Threshold for intake reporting. This allows the system to ignore small anomalies like 1% calorie excess.
6. Whether or not to see possible adverse effects of their dietary choices (e.g.: consequences of calorie excess/deficit)

Username and motivation are injected in the report, to make it feel more personal, while the other elements are used for content selection and tailoring. Reports are further enriched with the following insights:

1. Worst day: the day whose caloric intake was the furthest from the goal.
2. Nutrients ranking: nutrients are ranked and only the two furthest ones from the goal are shown.

\(^4\)Code available at: https://bitbucket.org/uccollab/diet-tailoring/
3. **Food analysis**: for each nutrients, the food which provided most of it is listed.

4. **Comparisons**: if previous week data are present, intakes are compared and the eventual improvement/worsening is shown.

Finally, we adopt Affective NLG (de Rosis and Grasso, 2000; Mahamood and Reiter, 2011; Piwek, 2002), framing the document as positive-toned. This includes expressing comfort in case of negative developments and congratulations for positive ones (e.g.: calorie intake improved/worsened). Each report referred to the past week. An output example can be seen in Figure 2.

4 Experiment setup

We evaluated the effect of our reports on the diet and emotional state of users in a 2-weeks experiment. A total of 81 participants were recruited (see Section 7 for details). Population demographics can be seen in Figure 3.

Participants were trained in using MFP and asked to log their meals through the app for the following 2 weeks. They were then randomly split into two groups: "Report group" ($n = 43$) and "Control group" ($n = 38$). Participants in report group received one report at the end of each week, while control group could only see the insights provided in MFP.

About 60% of the participants (from both groups) agreed to fill-in a weekly PANAS questionnaire (Watson et al., 1988) that we used to monitor their emotional/affective state. PANAS consists of 20 mixed positive (e.g.: "Attentive", "Proud", "Strong" etc...) and negative (e.g.: "Hostile", "Guilty", "Scared" etc...) words. Users score
Figure 4: Weekly PANAS questionnaire, as it was administered during the experiment

| Positive and Negative Affect Schedule (PANAS-SF) | Very slightly or not at all | A little | Moderately | Quite a bit | Extremely |
|-------------------------------------------------|-----------------------------|---------|------------|-------------|-----------|
| PANAS 1 Interested                               | 1                            | 2       | 3          | 4           | 5         |
| PANAS 2 Distressed                               | 1                            | 2       | 3          | 4           | 5         |
| PANAS 3 Excited                                 | 1                            | 2       | 3          | 4           | 5         |
| PANAS 4 Upset                                   | 1                            | 2       | 3          | 4           | 5         |
| PANAS 5 Strong                                  | 1                            | 2       | 3          | 4           | 5         |
| PANAS 6 Guilty                                  | 1                            | 2       | 3          | 4           | 5         |
| PANAS 7 Scared                                  | 1                            | 2       | 3          | 4           | 5         |
| PANAS 8 Hostile                                 | 1                            | 2       | 3          | 4           | 5         |
| PANAS 9 Enthusiastic                            | 1                            | 2       | 3          | 4           | 5         |
| PANAS 10 Proud                                  | 1                            | 2       | 3          | 4           | 5         |
| PANAS 11 Irritable                              | 1                            | 2       | 3          | 4           | 5         |
| PANAS 12 Alert                                  | 1                            | 2       | 3          | 4           | 5         |
| PANAS 13 Ashamed                                | 1                            | 2       | 3          | 4           | 5         |
| PANAS 14 Inspired                               | 1                            | 2       | 3          | 4           | 5         |
| PANAS 15 Nervous                                | 1                            | 2       | 3          | 4           | 5         |
| PANAS 16 Determined                             | 1                            | 2       | 3          | 4           | 5         |
| PANAS 17 Attentive                              | 1                            | 2       | 3          | 4           | 5         |
| PANAS 18 Jittery                                | 1                            | 2       | 3          | 4           | 5         |
| PANAS 19 Active                                 | 1                            | 2       | 3          | 4           | 5         |
| PANAS 20 Afraid                                 | 1                            | 2       | 3          | 4           | 5         |
Table 1: Diet outcomes per group (after two weeks). For each group, we report how many participants got closer to their dietary goals.

| Goal       | Report group | Control group | p-value (χ²) |
|------------|--------------|---------------|--------------|
| Calories   | 42%          | 23%           | ≈ 0.23       |
| Nutrient 1 | 56%          | 33%           | ≈ 0.16       |
| Nutrient 2 | 40%          | 42%           | ≈ 0.43       |

Table 2: Diet outcomes per group (after two weeks): we report participants average improvement in terms of distance from dietary goals (for calories and the nutrients that were mentioned in the report). For distance from goal, a decrease is considered and improvement.

| Goal     | Report group | Control Group | p-value (t-test) |
|----------|--------------|---------------|-----------------|
| Calories | +1.78%       | +6.53%        | ≈ 0.14          |
| Nutrient 1 | -25.92%     | -29.60%       | ≈ 0.17          |
| Nutrient 2 | -10.74%     | -17.36%       | ≈ 0.76          |

Through this setup, we inspected the following research hypotheses:

**Hypothesis 1 (H1):** Participants in report group improved their diet (in terms of caloric and nutritional intakes) more than control group.

**Hypothesis 2 (H2):** Participants in report group improved their positive affect score more than control group.

**Hypothesis 3 (H3):** Participants in report group improved their negative affect score more than control group.

While H1 is comparable to classic diet-coaching evaluation, we introduce H2 and H3 as a novel investigation of the communicative potential of these tools, related to users’ emotional state. For H1 we check the initial distance between MFP goals (for calories and nutrients) and user intake. Then, we verify if, at the end of week 1 and week 2, participants got closer to said goals. For nutrients, we consider the two most unbalanced ones (those that could be seen in the report). For H2 and H3 we monitor weekly PANAS scores (PA and NA) for each group. Since no group had access to reports when completing PANAS at the end of the first week, we use this value as a starting point. Then, we check differences at the end of week 2 and overall (from the start of the experiment).
5 Results and discussion

In terms of dietary outcomes, we obtained mixed results, but none of these were significant. In fact, the majority of participants improving calories and the first most unbalanced nutrient were in report group, but a chi-squared test revealed no significance (see Table 1). Both groups worsened their calories intake and we saw the biggest improvement in control group for nutrients (see Table 2). Again, a t-test revealed that none of these results is statistically significant. People in the report group were more likely to improve, while people in control group showed the biggest improvements, but a longer experiment is needed to assess whether reports (or their absence) played a role in this. With these results, we reject H1. However, it is safe to assume that reports didn’t worsen the effectiveness of MyFitnessPal.

On the other hand, PANAS analysis gave us more interesting results. Initially, we verified through a t-test that the two groups shared similar initial PA (average difference = 0.1, \( p = 0.96 \)) and NA (average difference = 1.7, \( p = 0.51 \)). Then, we checked how scores changed for both groups. PA and NA were checked at week 1, week 2 and across the whole experiment. The report group showed bigger improvements, both in terms of PA and NA (see Figure 5).

The report group showed (through t-test and Sidak’s p-value adjustment) a significantly bigger improvement for PA on the second week (\( p = 0.04 \)) and for NA across the whole experiment (\( p = 0.04 \)). Generally, the report group improved both scores more than the control group in any other situation, but only in these two cases the p-values were statistically significant. These results tell us that the report group tended to experience significantly:

1. More positive feelings during the second week
2. Fewer negative feelings across the whole experiment

than the control group. It is interesting to see PA significantly improving during second week. Since PANAS was administered before each report delivery, that was the first time that the report group could express their emotional state after reading a report.

The control group generally showed worse behaviour: PA greatly worsened during second week, while there was a slight improvement across the whole experiment (but much lower than the one experienced from the report group). NA consistently worsened in both cases. This tells us that the control group experienced a heavier emotional load during the experiment. We hypothesise that this is related to the cognitive load: the control group had to figure out how to interpret MFP charts and numerical data, while the report group was helped by the explanation provided in the generated text. Moreover, nutrients ranking helped participants from the report to focus on a limited amount of elements. In contrast, participants from the control group had to pay attention to calories and each nutrient. We also checked whether we could find some differences in the emotional state during the first week, when no group had access to the report. We observed a bigger PA improvement in control
group ($\Delta = 2$) than in report group ($\Delta = 0.72$). The opposite happened for NA, with the report group improving it ($\Delta = -2.04$) and control group slightly worsening it ($\Delta = 0.13$). None of these was statistically significant. Considering the lack of reports, in this case, we can assume that the cognitive load was similar. Overall, we could see a significant improvement in emotional state for the report group (PA in the second week, NA overall). With these results we confirm H2 and H3.

Final feedback (Figure 6) was mostly positive. The lowest scores belong to the help in changing diet, which could also be related to the experiment duration. When given the chance to express a comment on the system, many participants asked for charts and graphical elements which could have improved understanding. This result aligns with previous research (Law et al., 2005; Molina et al., 2011; Gkatzia et al., 2017), suggesting that a combination of visual features and textual communication could be the most effective approach.

6 Conclusion

In this paper we evaluated the effects of augmented communication in diet-apps using Affective NLG, tailoring and persuasive communication techniques. Unlike previous work in evaluating diet-coaching systems, we did not look only at dietary outcomes. Since diet is influenced by psychological factors we introduced a novel evaluation by adopting a validated psychometric tool (PANAS). We inspected whether our reports could play a role in improving users’ affective state.

Our hypotheses were confirmed, as we found that participants who read the report experienced more positive emotions and fewer negative ones. We also saw the opposite in most cases for the control group. Our work has shown that improved communication can reduce the impact of emotional load on dieting. Most importantly, we showed how important it is to consider the psychological component when designing, developing and evaluating communication systems, in diet-coaching and other domains. We could not see an effect on diet itself, which encourages us to run a longer trial (one month or more) in future, to further assess the effectiveness of our communication strategy. However, we ran just a basic assessment on the psychological side. We plan to expand our evaluation procedure by combining multiple tools and scales. As our previous work pointed out, stress is one particular factor that could be worth monitoring (Baloccu et al., 2020b), so this is one of the main directions we intend to follow. We also could not run any kind of ablation test. This leaves us with the conclusion that our approach did work.
but without any insights on how different elements (affective NLG, persuasion or text tailoring) contributed.

Based on the feedback from users, more than just text is required to improve the system. We leave this as future work. Still feedback was largely positive with regards to textual features and comprehension. We note that the questions were not accompanied by rigorous definitions of “readability”, “accuracy” and others. Users expressed feedback based on their own personal idea of these concepts and this raises questions regarding the reliability of the results. We consider the overall uniformity of ratings as an indicator that all participants had a “common” definition of the proposed concepts. Still this uncertainty contributes to a well-known problem in human evaluation (Howcroft et al., 2020), so we commit to more rigorous and uniform metric definitions in future.

7 Ethical considerations

This section sums up the procedure we adopted to ensure the ethical compliance of our experiment.

7.1 Preliminary review

Before starting the experiment, procedure and materials were carefully reviewed by the University of Aberdeen Ethics Board. Our experiment proposal was accepted without major revisions.

7.2 Recruitment

Participants were recruited through physical interaction on campus (by flyer distribution), department mailing list or social media public posts. No recruitment qualification was specified, beside the lack of health conditions that are known to affect individuals diet. This includes pregnancy, suffering from eating disorders or psychological treatments. This was done since our system has been developed to work in “standard” situations, while the aforementioned cases would have pose high risks for participants. Participants were showed a consent form containing all the information regarding the experiment procedure. All participants had to confirm their acceptance of these conditions (through check-boxes and signature) in order to proceed with the experiment. Participants were given an email contact in case of problems during the experiment.

7.3 Pay and workload

Each participants received £20 (or 20€ for participants outside of UK) at the end of the experiment, as a token of gratitude for their contribution. Access to the token of gratitude was bound to the compliance of the following condition:

1. To complete the experiment (that is, using MFP for two weeks; giving the final feedback)

2. To provide, to the best of their capabilities, the most complete and accurate food diaries they could.

Requirement 1) also included PANAS forms for those participants who agreed to do so. For 2) participants were supervised and given support about meal logging and eventual missing entries. Participants were also informed of the possibility of abandoning the experiment (up to the point of data analysis), which would result in exclusion from receiving the token of gratitude.

7.4 Data protection and storage

A MFP account for each participant was generated through temporary email that was in no way linked to their identity. Following the experiment conclusion, all accounts have been blocked. Data have been safely stored and anonymised.

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