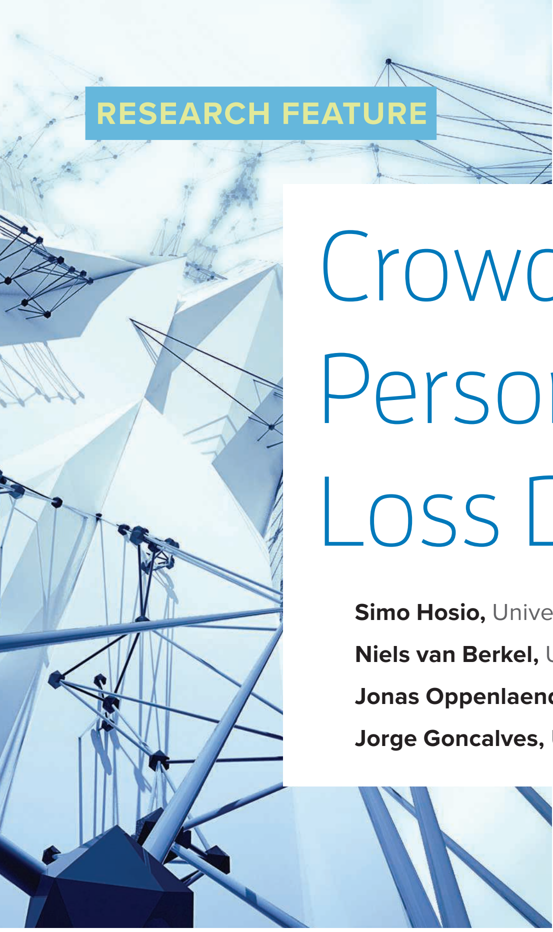

Crowdsourcing Personalized Weight Loss Diets

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The Diet Explorer is a lightweight system that relies on aggregated human insights for assessing and recommending suitable weight loss diets. We compared its performance against Google and suggest that the system, bootstrapped using a public crowdsourcing platform, provides comparable results in terms of overall satisfaction, relevance, and trustworthiness.

Obesity is a growing health problem around the world and has been described as a global epidemic by the World Health Organization. Not only is being overweight a psychologically sensitive issue, but it has been shown to negatively affect health in a number of ways, including accelerating aging or increasing the risk of diabetes and heart conditions. Examining the issue strictly through the academic lens, two aspects matter in losing weight: diet and exercise. However, previous work has shown that the former is substantially more important.[1] Yet there is no consensus even among scientists on what is the optimal diet for losing weight (consider, for example, the constant battle between low-carb and low-fat diets). As a result, one identified problem in the dieting world is information overload.[2] There are simply too many diets to choose from.

In this article, we present The Diet Explorer (TDE), a crowd-powered tool that exploits crowdsourcing and wisdom of the crowd[3] in first assessing and then recommending personalized weight loss diets. Using paid labor from Prolific Academic (https://prolific.co/), a crowdsourcing platform designed for academic studies, we assessed all 21 major weight loss diets listed in *Wikipedia* at the time of this study across six distinct evaluation criteria. Then, using the same source to hire participants, we conducted a user study to compare TDE against Google in discovering personalized weight loss diets. We consider Google as a fair yardstick in this case since people increasingly turn to online resources to find health-related information.

Our results validate that TDE can be used to quickly offer personalized weight loss diets that meet the user's needs much in the same way as Google but faster and without its clutter, advertisements, and other identified

Digital Object Identifier 10.1109/MC.2019.2902542
Date of current version: 15 January 2020

pitfalls. Finally, we make a technical contribution by providing a considerably improved, reimplemented version of TDE in the plug-in repository of the world's most popular online content management system, WordPress. Installing the plug-in version of TDE is thus a one-click process, and webmasters can use it for helping their visitors to discover diets and donate data for science.

TDE

Background and related work

Losing weight is challenging. Both a proper and balanced diet and exercise help, but of those two, diet has been shown to matter more.[1] Yet, as evident from the endless amount of dieting fads and advice, choosing a diet to begin with is extremely challenging and confusing. To this end, crowdsourcing has emerged as an excellent method to aggregate knowledge that can then be used in recommending suitable and trustworthy options: to basically offer decision support.[4,5]

Crowdsourcing has several advantages in decision support, such as collecting large numbers of potential solutions and evaluating their quality to suggest the best ones.[6] Related to this, TaskGenies[7] uses online crowds to create action plans that help people to be more productive in everyday chores. In general, the more specific plans the participants were given, the more productive they became. In a similar vein, PlanSourcing demonstrated how friends and strangers alike may be leveraged to create plans that lead to behavioral changes in the form of better personal decisions.[8] This study highlights an interesting characteristic, or benefit, of crowdsourcing: sometimes it is easier to ask for time-consuming help from strangers than friends. Finally, Hosio et al.[4] discussed a lightweight decision support tool that helps collect solutions to any problem and rates those solutions in terms of different criteria.

In this article, we leverage crowdsourcing to assess weight loss diets across a variety of criteria, using a data structure similar to the one described in Hosio et al.[4] In other words, we modeled human-contributed information on diets across a set of criteria by crowdsourcing multiple ratings per each diet-criterion pair. This crowdsourced information repository—a snapshot of the cumulative knowledge of the respondents—was then used to bootstrap a crowdsourced system that allowed users to discover diets that best match their personal preferences, described by a set of optimal/desired criteria values.

However, it is important to note that from a nutrition science perspective, we do not consider whether these diets work optimally and for whom. Our interest lies in matchmaking requesters with suitable diets using a crowdsourced approach and investigating how the approach system compares to the contemporary de-facto way of discovering diets, Google.

Implementation

TDE is a lightweight web-based tool that can be embedded on any website using a standard HTML iFrame tag (we describe the Wordpress plug-in later). TDE was implemented using HTML, JavaScript, PHP, and MySQL. In essence, it is a crowd-powered decision support system[6] that collects data on a question and provides answers by querying the data. As we collect several subjective, independent ratings for each of the available diet-criterion pairs, the resulting knowledge is based on the wisdom of the crowd, where the crowd is the people who assessed the pairs. Specifically, in the health information field, a similar approach has been successfully used in the past to recommend and capture data on lower-back pain treatments.[5]

An important consideration with any embeddable tool such as ours is the surrounding context, in other words, the website. The context always plays a role in user perceptions. To keep our study design tidy, we deployed TDE as a solo installment on a blank page online. There was no context to skew the users' opinions about the tool and its functionality. Instead of a website that would normally introduce the tool, we deployed an additional short splash screen before loading TDE for the users and set out to examine how TDE succeeds in recommending diets. From the end users' perspectives, TDE consists of two main conceptual stages: one for assessing different weight loss diets and one for discovering personalized diets among all of the previously assessed diets. These are separate interfaces, however, and in the study presented in this article, each participant only used one or the other, not both.

Assessing diets

With TDE, every diet is assessed against a set of different criteria, using a slider input element that maps to a numerical scale from zero to 100 [see Figure 1(a)]. This corresponds to how well the diet in question intuitively performs in terms of the criterion being assessed. The numerical value of the scale is displayed as the user moves the handle and is supplemented with a verbal scale to help the user understand the value. TDE can host an arbitrary number of diets and any arbitrary criteria. A diet in TDE consists of a short title (for example, "The Paleo Diet"), a longer description of the diet ("The Paleolithic diet is predominantly focused on consuming only foods presumed to have been the only foods available or consumed by humans during the paleolithic era [...]"), and a hyperlink to an external information source about the diet (we used *Wikipedia* links). In a similar vein, a criterion consists of a short title (such as "Rapid weight loss potential") and a longer description.

The data model for storing structured subjective knowledge on arbitrary questions has been pioneered earlier in crowdsourcing settings.[9] The individual ratings are independent and from different people and therefore usable in estimating the relations on each diet-criterion pair, based on the theories behind wisdom of the crowd.[3] The results of the tool are as accurate (or inaccurate) as the people bootstrapping it with their knowledge.

Discovering weight loss diets

Once data on every diet have been collected, TDE is ready to be used for discovering diets that best match the user's preferences. In the discovery interface, the user indicates personal importance values for the same criteria that were used to assess the diets. All the criteria are again represented with sliders, and the same verbal cues were provided to help users with their thought processes. In Figure 1(d), the user seeks to discover diets that, according to the crowd, have very high potential for rapid weight loss and provide all of the nutrients needed for general well-being. The interface also allows the user to reset the sliders and start over. The wordings of the criteria were also slightly altered since assessing

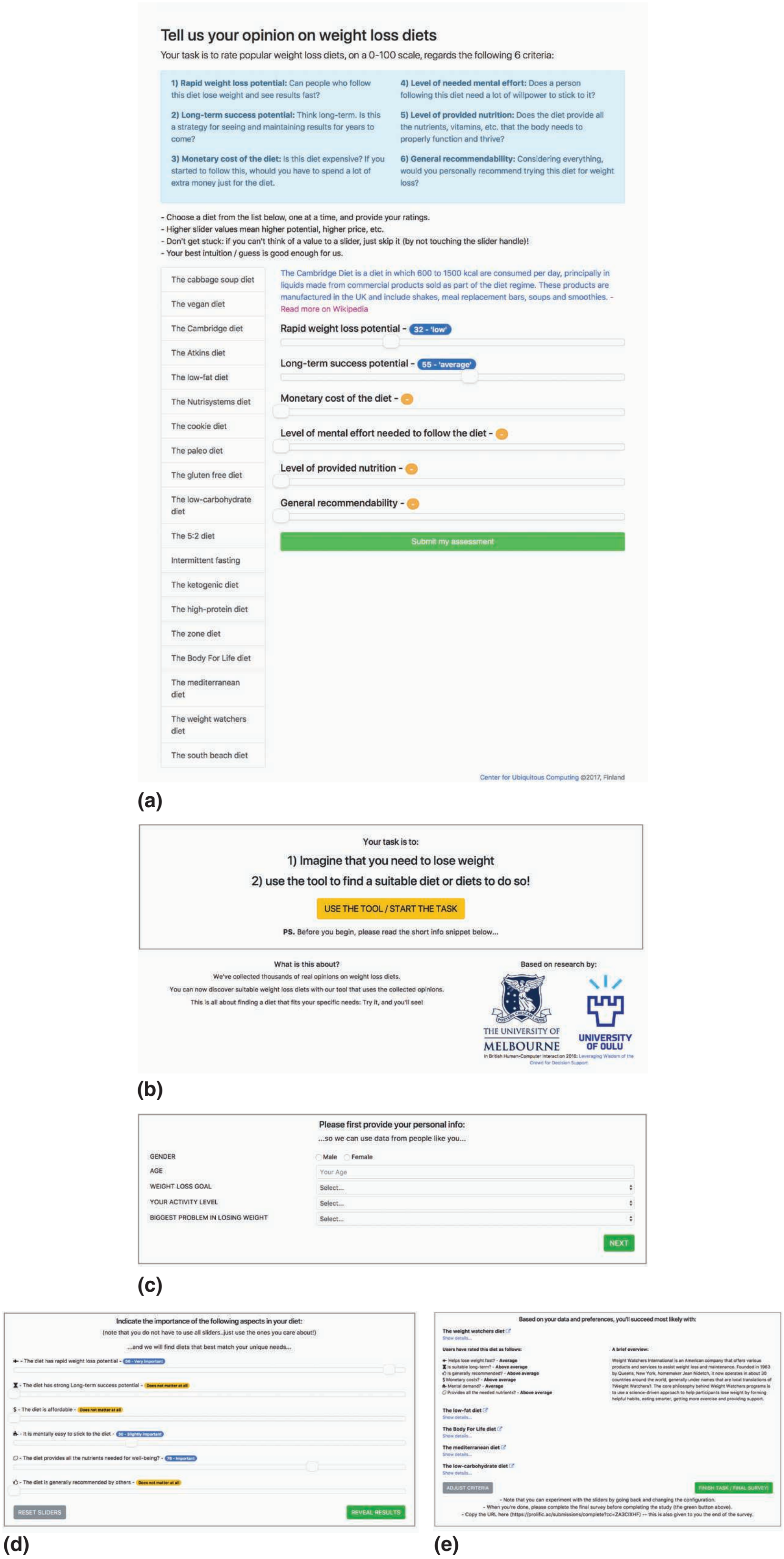

FIGURE 1. The screenshots of the TDE platform: (a) the interface to assess diets across different criteria, (b) the splash screen used in the experiment, (c) the personal information collection screen, (d) the ideal criteria configuration screen, and (e) the results screen depicting the top-five matches (diets) and links to read more about them.

diets and indicating the importance of the assessment criterion are two different tasks that require a different choice of words. The original criterion "monetary cost of the diet" was also inverted here since, when asking users for their appreciation of a characteristic, we considered affordability as a more intuitive metric to use.

Clicking the "Reveal Results" button initiates the query and takes the user to see the best-matching results. The results interface [depicted in Figure 1(e)] lists the five best-matching diets in the left column. The underlying matchmaking algorithm works as follows. Instead of absolute values of the criteria (as was the case in the assessment stage), the user sets importance coefficients to the criteria, ranging from zero to 100. The user-set coefficients are then multiplied with the crowdsourced ground truth estimates of each of the diets in the knowledge base. The tally of these scores becomes the diet's final grade, and the ones with the highest score are the diets that best match the user's requirements. In the interface, the user can also follow a link to the external information source (configurable per each diet) by clicking the icon displayed after each short title. Finally, the interface allows the user to go back and alter the desired configuration to explore how the results change, a process described as "what if analysis" in decision support systems literature.[10] For the study, we also included a button to conclude the task and take the user to a final questionnaire.

For the purposes of this article, we included an additional step to TDE for collecting personal information [Figure 1(c)] to make the user feel like the system considers more attributes than just the criteria values. We asked for their weight loss goal, general activity level, and biggest problems in losing weight. However, we did not use the personal information in the matchmaking algorithm. This was explained to the user at the end of the study. We also included the logos and branding of our institutions (Figure 1(b)] as knowledge of the origin is one of the very initial steps to information trust.[11]

THE EXPERIMENT

We probed TDE's potential with an experiment that required the user to imagine they needed to lose weight and then simply find the best weight loss diets for themselves by using either TDE or Google. For our between-subjects user study, we recruited two batches of users: one batch used TDE and the other batch used Google. We used Prolific Academic for the recruitment of participants in both conditions. Both conditions ended in a survey online, where the first step was identical in being able to compare TDE to Google in finding diets. The participants using Google were instructed to search online for a minimum of five diets that they identify as the best for their needs. The participants were instructed to copy and paste the URLs of their chosen five to a text area we provided as part of the splash screen, as proof of task completion.

Criteria and diets used in TDE

We acknowledge that the choice of diets and criteria crucially affects the outcome of the experiment. For the study, we chose to list all 21 weight loss diets available at *Wikipedia* at the time of the study as a fair approximation of the set of most popular diets in the market. As for the criteria, we independently examined various weight loss forums and magazines online, focusing solely on sites that host user-generated content: question and answer sites, weight loss and fitness forums, and social (Web 2.0) platforms. We then discussed the most commonly encountered criteria encountered and decided to include the following six criteria that were all explained to the participants in more detail:

1. rapid weight loss potential
2. long-term success potential
3. monetary cost of the diet
4. level of mental effort required to follow the diet
5. level of provided nutrition
6. general recommendability.

The end user survey

The shared first step of the end user survey, hosted in Google Forms, that participants in both conditions were required to complete started with a seven-point Likert scale[12] with the following items:

- general trustworthiness of the obtained results
- relevance of the results to the used search parameters
- considering everything, the satisfaction level of the results for the task at hand
- speed of the process
- the likelihood of the user choosing one of the discovered options as the first choice of diet, if the user was supposed to start dieting for weight loss right now.

The items were labeled from "not at all" to "extremely," and in addition to the Likert scale, we asked for the participant's demographic data. The second step of the survey was condition specific. For the participants who used TDE, we asked open-ended questions on which criteria (if any) are missing from the tool, how exhaustive/sufficient it covers the list of diets, if the users would recommend TDE to a friend who wants to lose weight, any positive or negative aspects observed, and finally, suggestions for improvement.

As mentioned earlier, for the participants who used Google, the first part of the survey was shared, and the second part of the survey focused open endedly on uncovering the specific pros and cons of Google in finding weight loss diets.

RESULTS

Before we could study finding diets with TDE, we needed to bootstrap TDE or populate the knowledge base on the diets chosen by us. For this purpose, we recruited 70 participants (47 female, 22 male, one other, average age 31.3) from Prolific Academic. The participants provided 8,607 ratings for the diets (an average of 68.3 ratings per each pair). In similar crowdsourced systems (such as Hosio et al.[5]), a far smaller participant number was shown to provide reliable results, so we argue that 70 is an adequate number in this case. While a more exhaustive analysis of the assessment is out of scope of this article, in Table 1, we present the three top- and bottom-rated diets (based on absolute numerical values acquired in the assessment stage) per criteria.

TABLE 1. A summary of the best- and worst-rated diets in the experiment.

	Speed	Duration	Cost	Mental effort	Nutrition levels	Recommendability
Top three	14 (82.2) 12 (78.5) 9 (75.0)	15 (72.2) 21 (64.7) 10 (63.1)	6 (74.3) 23 (72.9) 7 (71.6)	21 (92.4) 17 (75.8) 11 (75.0)	6 (66.2) 21 (63.5) 4 (63.5)	21 (68.6) 6 (64.1) 15 (60.3)
Bottom three	17 (39.8) 21 (32.4) 11 (2.6)	24 (24.4) 14 (15.8) 11 (1.6)	12 (22.6) 16 (20.7) 14 (5.3)	21 (51.3) 17 (50) 11 (10)	12 (25.5) 11 (12.4) 14 (5.8)	5 (25.4) 14 (7.4) 11 (2.4)

LEGEND

4	The Nutrisystem diet	15	The Weight Watchers diet
5	The cookie diet	16	Intermittent fasting
6	The Body For Life diet	17	The gluten-free diet
7	The paleo diet	18	The ketogenic diet
8	The vegan diet	19	The high-protein diet
9	The Atkins diet	20	The low-fat diet
10	The low-carbohydrate diet	21	The Mediterranean diet
11	The junk-food diet	22	The Zone diet
12	The cabbage soup diet	23	The Cambridge diet
13	The South Beach diet	24	The 5:2 diet
14	The Breatharians diet		

The values in parenthesis are means of the ratings given for the diets (based on the approximately 70 ratings given).

TDE versus Google in discovering diets

We recruited 41 participants (22 female, 19 male, average age 32.9) from Prolific Academic to discover diets with our tool. Thirty-seven of the participants indicated that they actually want to lose weight, making them a suitable audience for the evaluation since they are among the actual intended audience. Using manually paid bonuses, we ensured that everyone was paid U.K. £12–15 per hour for the work, to adhere to fair pay policies of Prolific Academic.

To compare the process with finding diets using Google, we recruited 40 participants (23 female, 17 male, average age 30.3) from Prolific Academic to find diets using Google, ensuring that these were new participants. Of these 40, 31 indicated that they want to lose weight. For the participants finding diets with Google, we used the same payment scheme as with TDE.

In analyzing the result data, we found no evidence of significant differences between TDE and Google in terms of

- trustworthiness of the discovered diets: averages 5.4 and 5.3, respectively
- their relevance to the used search parameters, in other words, criteria in TDE and search terms in Google: 5.3 and 5.6
- overall satisfaction with the discovered diets: 5.4 and 5.6
- acceptability of the results, that is, if the users would likely start with one of the discovered diets if they wanted to start losing weight now: 5.8 and 6.0.

In terms of perceived speed of the task, however, there was a significant difference in perception, as TDE was perceived as faster than Google in discovering diets with (6.2 and 5.1; Wilcoxon Rank-Sum test, $p < 0.01$). To summarize, TDE comes close to Google in performance across all other measured items and is better in the perceived speed of the search task. Indeed, only five of the 41 participants would not recommend TDE to their friends who want to lose weight (28 answered yes, and eight answered maybe).

Qualitative insights

Two of us first reduced the result to three clear overarching themes, the pros and cons of the two approaches and improvement suggestions to TDE. One of us was invited to verify the classification, after which we moved all of the items to a shared spreadsheet online and iterated the labeling process until all relevant comments belonged to one or more subthemes.

First, we noticed that participants frequently mentioned the clutter and advertisements present when using Google. While we were not surprised to see comments about the excessive amount of advertisements encountered with Google (and online in general—our participants only started with Google and ended up on third-party sites), the interesting finding here is how useful the ads seemed to be for certain participants. One said, "I find the promoted ads at the top of searches are actually quite useful in searching for new diet plans and they often show the best value options."

The ads were viewed as fairly accurate and actually contributing to the search rather than always viewed as a negative. This opinion was split, however, and more people still perceived ads as more harmful than good. One participant related, "Lots of adverts and misleading diet offers…" Another said, "There's SO MANY!"

Participants were generally aware of all of the false promises and companies "trying to get your money." Several participants were also concerned about finding potentially unhealthy or outright harmful solutions, such as diet pills and other such snake oils that are, in reality, some of the most lucrative dieting products available from the vendor's standpoint. During the past years, Google has done a laudable job in banning such products and their advertisement campaigns. The sites where users end up by employing the Google search engine are, however, a different playground. There, users are still exposed to all types of nonlegitimate dieting and weight loss offers. In other words, Google is practically helpless in this matter.

Overall, however, Google's search capabilities were found as impressive. "It's a good search engine capable of helping narrow down a large number of results if you're really specific in what you're looking for," read one comment.

The one thing that was clearly appreciated by TDE users was the straightforward approach of discovering diets to consider. Responses such as "quick" and "easy to use" occurred frequently. "I like how simple and easy it is. Also, I like the fact that you get multiple options," remarked a participant.

Two participants even reported finding diets they had not heard of before, and one commented that she is even going to try it after participating in the study. As for key problems with TDE, participants most often would have liked to see more information on the diets (for example, pork free or vegetarian recipes that would go together with the diet). One user said, "There was no accommodation for allergies or personal/religious restrictions. I don't want to be recommended a high-meat diet if I'm vegetarian, for example."

Other participants were disappointed by not finding diets that they enjoy eating (for example, curry) and took a very hedonistic stance in dieting. "It looks as if there would not be any enjoyment left in eating," one user noted. Such insights are great in understanding what goes on in the minds of people looking for diet options and thus in developing the next versions of TDE.

TDE as a reimplemented tool for science

While controlled experiments have their uses, we argue that the online equivalent of an uncontrolled field study, such as placing the tool as part of the existing fabric of the web, is a currently underexploited opportunity in health information-related experiments. Such an approach, if executed with care, will produce results with high ecological validity and help reach people who otherwise would be out of reach of academic studies.

With this in mind, and informed by the qualitative findings from our experiment, we converted TDE to a WordPress plug-in and added three new features: a featured diet option, a promotion box, and a data capture feature (detailed below). WordPress is the world's most popular content management system and currently powers tens of millions of websites online according to estimates, or over 30% of all blogs and websites in existence. The new features of TDE are available only in a commercial version of the plug-in, but we offer any nonprofit academic organization a free-forever license for the premium version. The new features are detailed next.

Featured diet option. Similar to native advertising online, we provide a placeholder where the manager using the plug-in can control what is shown as the fifth discovered diet option. If no featured diet is provided in the plug-in settings, in the WordPress admin area, or if this option is turned off, the plug-in simply shows the fifth best-matching option [Figure 2(e)].

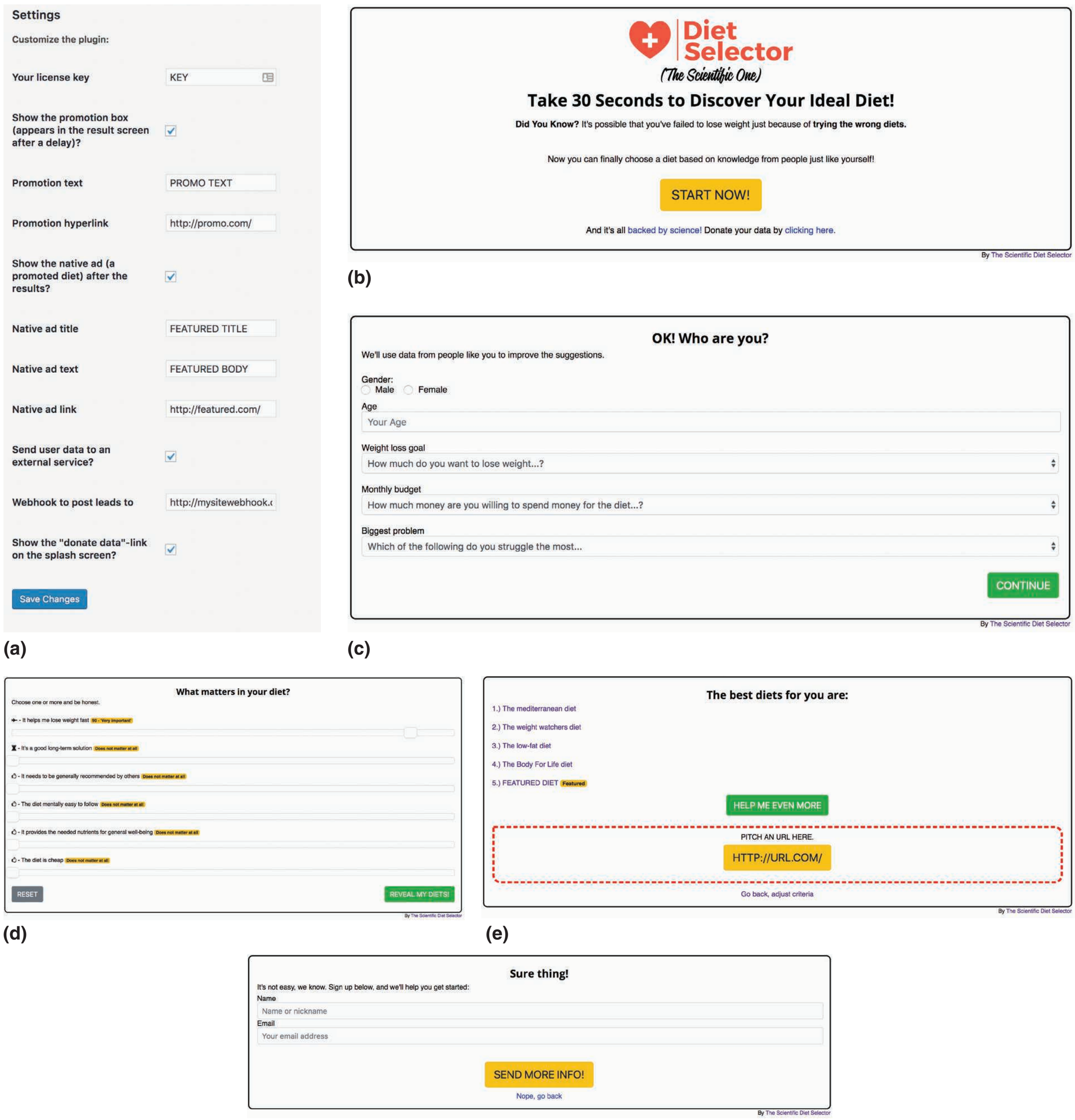

FIGURE 2. The TDE (rebranded as The Scientific Diet Selector), reimplemented as a WordPress plug-in: (a) the back-end settings panel to customize content containers and set the webhook (or switch the customizable features on/off), (b) the intro screen with links to read more and donate data to science, (c) the user data collection form, (d) the criteria selection form to determine the characters of ideal diets, (e) the results screen with a featured customizable diet placeholder and a promotion box, and (f) a lead-collecting form for integration with any back end or customer relationship management system for follow-up studies and surveys.

Promotion box. Second, we provide a promotional area surrounded by a clear visual border in the results screen. The promotion box can contain both text and a link. As depicted in Figure 2(e), the text is placed before a big yellow button that opens the URL in a new browser tab. Here, any additional resources relevant to the user's interests can be promoted. In the case of scientific studies, this area could be used, for example, to deploy different conditions in a study, direct the user to a survey, or simply invite the user to another study by using the plug-in as the magnet to get the user interested in exploring different options in a fun way.

User data capture and follow-up. Finally, the most powerful feature of the plug-in, depicted in Figure 2(f) and accessible through a button in the results screen [Figure 2(e)], is the user data capture feature. This screen asks for the user's name (or nickname) and an e-mail address. The plug-in settings screen [Figure 2(a)] allows for setting a webhook destination, where all of the data are sent when the users request more help. For academic purposes, these texts can be changed to reflect the study's purpose. Once the user requests more help or follow-up, the plug-in sends to the webhook in a JSON payload

- the responses the user gave in the personal data collection stage [Figure 2(c)]
- the used search parameters (criteria configuration)
- the user's name and email address
- the top results that the used criteria yielded.

This feature can be used in automated fashion to respond to users' requests for more details on the chosen diet, a key finding in our qualitative results. This feature is particularly useful in many types of experiments, including follow-up studies where the user data are inserted into a customer relationship management system and the user is later invited back to, for example, fill in periodical surveys or participate in new studies.

DISCUSSION

In the bigger picture of obesity, tools such as ours are not a panacea. However, given the magnitude of the problem, no stone should be left unturned in exploring how to offer suitable lifestyle choices to people. And discovering diets is only one part of the puzzle. Diets differ. There is no clear academic consensus of what diet one should follow, and a diet that works for one person might not work for another. Nevertheless, TDE was created to let people discover and consider diets that may fit their needs, based on assessment by real people. By design and choice, we detach from the scientific debate of the diets' effectiveness and instead provide users a chance to discover a set of diets that a crowd (be it whatever it is) has assessed as suitable in terms of the search parameters used (the criteria).

We consider our results not as perfect but promising. Using only the diets from a ranked list on *Wikipedia* and a public source for participants to assess them, we were able to bootstrap TDE to a state where the discovered diets compared relatively well against the ones discovered with Google. Moreover, TDE was seen as a rapid and straightforward tool for this. For the very same reason, we see TDE as a potential platform for conducting academic research and highlight the plug-in as a prominent output of this article.

Design opportunities

The lack of details and specific information in the diets was perhaps the one thing that bothered the TDE users the most. As the concept relies on crowdsourcing, we are exploring how to use the plug-in to support users contributing extra information including food plans, links to online resources, or gluten-free or vegan options of the same diet. Most likely this will require exploring incentive mechanisms and carefully considering where this data collection happens (either on a third-party website or within the plug-in itself).

While in this study with TDE we deliberately detached from scientific debate on the diets and their efficiency in losing weight, we could bootstrap several versions of the tool. Several end users mentioned that the diets were all known to them already, and more could be added. The study here had a limitation in that it only considered diets from *Wikipedia*. Currently, we manage the diet knowledge base in a centralized fashion, but we already allow adding new diets to it. However, we lack means to derive a solid academic understanding of the diets. Therefore, hiring a pool of actual nutrition/dieting experts to rate the diets would offer great value to complement the peer-sourced knowledge. We need to work on ensuring the tools' scalability: how many users we can serve and whether the tool should gain wide adoption.

An addition we already support but do not offer as a service in the plug-in is a precreated follow-up sequence that motivates the users to follow a diet—to stick to the selected diet—as choosing a weight loss diet really is just the start. Stickiness was also suggested to be added as a criterion by several participants. To this end, researchers can implement

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a motivational follow-up sequence that the user can subscribe to directly from the plug-in by using the built-in webhook integration feature.

In this article, we presented TDE and our initial study utilizing it. We find TDE to be a promising system for discovering diets that provides a fair alternative to Google, especially for people new to dieting and who just want to quickly get an overview of diets that may be suitable. As the most important contribution of this article, we highlight the WordPress plug-in available in the public repository for the community to use.

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