Increasing Quality of Life Awareness with Life-Logging

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Abstract. Life Meter is a health mobile application that helps users raise awareness of their quality of life by showing indicators derived from life-logs collected by commercial wearable trackers, smartphone sensors, and manual input. We describe the general infrastructure we developed for the collection and fusion of life-logs, how the quality of life indicators are calculated, and the GUI of Life Meter. The results of a live-user study show that our application has high functionality and subjective quality, and, according to the users, it increases their awareness of the importance of monitoring quality of life.

Keywords: Quality of life · Life-logging · Mobile app · User study

1 Introduction

Mobile applications have a great potential of becoming useful routine instruments for monitoring our health and quality of life (QoL). According to a recent survey conducted in the US and involving 500 healthcare professionals and 1,000 health mobile app users [7], healthcare professionals think health apps will improve healthcare, in particular for patients with chronic diseases. The survey also revealed that most people use the apps as a lifestyle choice to track their physical activity or to get help lose weight, and that the use of apps to support healthcare is growing. In general, more and more people are willing to use mobile devices and wearable trackers to acquire personal health data. They see mobile "personal agents", which are able to summarize the collected data into meaningful knowledge and present it when needed, as useful tools for achieving better self-management of their health conditions, in particular adherence to long-term therapies [12].

Despite this very promising scenario, also the most passionate members of the *Quantified Self*, a movement of people who use self-tracking technologies to collect and explore personal (numeric) data about their daily lives [4], encounter

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barriers as lack of time and motivation as well as difficulty in data integration and interpretation [22]. Moreover, self-tracking is subject to several common pitfalls such as tracking too many things, not tracking triggers and context, and lack of scientific rigor [11].

Increased automation in tracking, fusion, analysis, summarization, storage, and context-dependent presentation of valuable personal data would certainly reduce barriers and risk of common pitfalls, and it would also contribute to the further diffusion of health apps. This can also be the basis for the development of innovative mobile healthcare *Proactive Advisory Systems (PASs)* [23], able to provide people with personalized information and advice, in order to promote healthier behaviors, well being, and adherence to medical treatments. This paper gives a contribution in both these directions. We describe a general infrastructure (a preliminary version is presented in [30]) able to acquire, fuse, and store life-log data from multiple channels (*Fitbit* [2] wearable trackers, *Android* smartphone sensors, and manual input); this infrastructure includes web services that third-party applications can invoke to retrieve various types of row data and inferred higher-level summaries. We also present *Life Meter*, a health mobile application that helps users better assess their QoL. *Life Meter* exploits the services of our generic infrastructure and presents personalized QoL indicators to users on a mobile GUI that shows the current values of the indicators, as well as their summaries over the last weeks. We focus on four QoL indicators that are useful for implementing PASs for healthcare: *activities* performed; *sleep* quality; level of *fatigue*; and *mood.* For example, a PAS for assisting allergic patients in the management of their disease treatment [23] could cross reference these QoL indicators with the treatment data in order to highlight the treatment efficacy or the negative effects of interrupting the treatment.

We present here the results of a live-user evaluation aimed at benchmarking *Life Meter* against the *Mobile App Rating Scale (MARS)* [28]. Our application proved to have higher functionality and subjective quality than the average of a benchmark of 50 health mobile applications. Moreover, the users indicated that *Life Meter* is likely to increase the awareness of the importance of monitoring QoL and the understanding of QoL indicators.

In the next section, we position our research with respect to the existing literature. Section 3 describes the generic infrastructure for multi-modal life-logging we have designed and implemented. Section 4 presents how the QoL indicators provided by *Life Meter* are calculated from users' life-logs, and how they are presented on the GUI. In Sect. 5, the evaluation of *Life Meter* is presented. Finally, Sect. 6 summarizes the lesson learned from this research and sketches future work.

2 Related Work

The research community has demonstrated a growing interest in the application of life-logging and mobile devices for the realization of healthcare services [21]. The provision of effective services should be based on the availability of robust and generic life-logging infrastructures, able to gather data from multiple devices and sensors, leverage it to infer higher-level knowledge of patient's health status, and present this knowledge to patients via usable user interfaces. Examples of infrastructures for life-logs acquisition that are not specifically dedicated to healthcare are *MyExperience* and *UbiqLog*. *MyExperience* [16] is a mobile system that uses both automatic logging from mobile phone sensors and applications, and context-triggered sampling of experiences by directly asking users. *UbiqLog* [25] is a lightweight, configurable, and extendable framework that uses the mobile phone for life-logging. Compared to these frameworks, our approach has the advantage of integrating data streams from smartphone sensors, wearable trackers, and manual input. This allow to have more comprehensive life-logs, able to better cover the users' activities during the day, also when the users do not carry the smartphone, for example when exercising.

Recently, projects have also focused on life-logging infrastructures dedicated to healthcare, with an approach similar to ours. For example, the research presented in [14] investigates the possibility of collecting and aggregating life-logging data with the use of wearable devices, mobile apps, and social media. Upon this infrastructure, *MyHealthAvatar* [27] is a web site built to empower citizens and patients through a number of health related services. A life-log collaboration framework on Android platform for the healthcare service infrastructure is proposed in [20]. The framework provides a collaboration mechanism between life-logging devices by different vendors and consists of three layers: the data logging layer, the data mining layer, and the data service layer. The framework was applied to develop health screening forms. *SenseSeer* [8] is a generic mobile-cloud-based life-logging framework that supports customizable services, such as personal health monitoring, location tracking, lifestyle analysis, and tourism focused applications. In particular, the *My Health* service is a personal healthcare-oriented web application that allows the user to track and visualize her physical activities. All these infrastructures were evaluated only performing some robustness test or by asking informal feedback to colleagues and not via a well structured user-study as we did for *Life Meter*. Performing rigorous user-study is fundamental for correctly adapting health mobile applications to users' needs [29], since it is increasingly difficult to readily identify and assess high quality apps [13].

Finally, it is worth mentioning that many commercial aggregators (e.g., *Zenobase* [6], *AddApp* [1], *TicTrac* [5], and *HealthVault* [3]) have been recently introduced, and this gives evidence of the popularity that self-monitoring is acquiring. These tools can usually aggregate and then show data from a wide range of sources. However, there is still need for extensive and rigorous user studies in order to evaluate their usability, efficacy and efficiency.

3 Life-Logging Infrastructure

The infrastructure we have developed for building users' life-logs integrates data continuously collected from wearable trackers, smartphone sensors, and manual

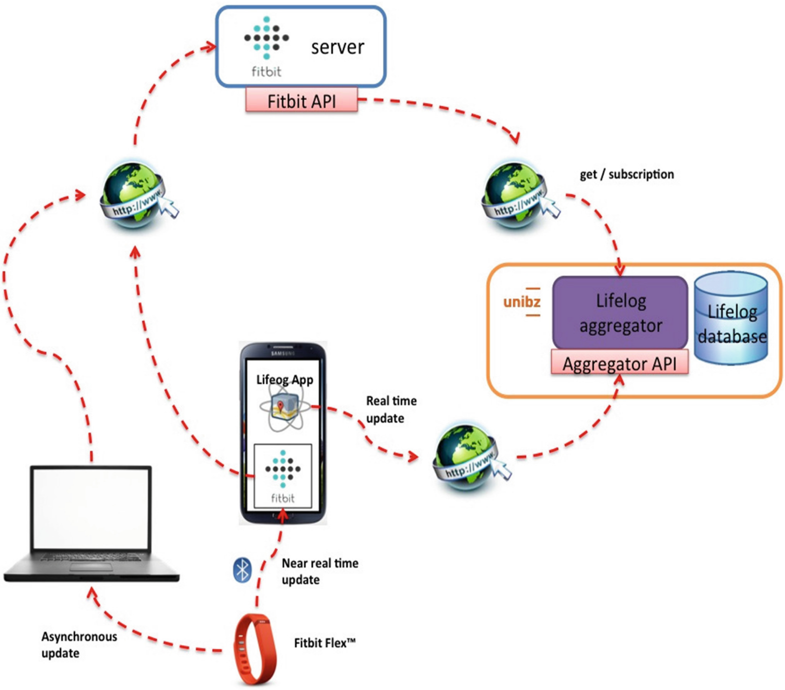
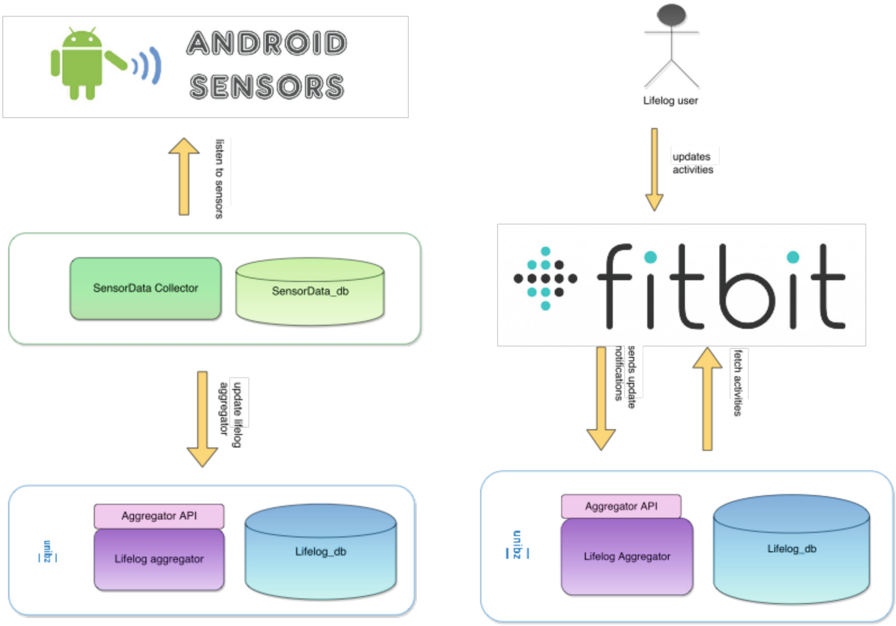


Fig. 1. Life-logging infrastructure.

input. For life-log, we intend the personal data generated by one's physical and digital activity (recorded by trackers and sensors) or manually entered by the user. The implemented system (see Fig. 1) automatically acquires information about what users do during the day. Data streams are collected from *Fitbit* [2] wearable trackers (we have experimented the infrastructure with *Fitbit Flex* and *Fitbit Charge HR*) and *Android* smartphones. While the tracker provides steps, burned calories, covered distance, heart rate, and sleep quality information, the smartphone collects information as performed calls, sent SMSs, position, and temperature. In addition, the user can manually input her mood in the system. All the collected data is exploited for the detection of QoL indicators. For example, phone calls to/from colleagues/work partners are signs that the user is probably working, or a variation of the resting heart rate from day to day can be used as a proxy of physical fatigue.

The life-logs are aggregated and stored on a dedicated server by two software components: a *Lifelog Service* and a server side *Lifelog Aggregator*. The *Lifelog Service* is developed for Android SDK 4.0+ and runs on the users' Android smart devices. It runs in the background, gathers life-log data from the device sensors, and periodically uploads it to the server. This is done by two always-active components (see Fig. 2(a)):

1. The *Sensordata Collector* monitors the sensors and stores their values in an internal database. In order to avoid draining the smartphone battery, the



(a) (b)

Fig. 2. Life-logs acquisition from smartphone sensors (a) and Fitbit server (b).

Sensordata Collector does not poll sensors for their status, but only reads new data when it is notified of a change in the sensor status.
2. The *Lifelog Uploader* starts at regular intervals (e.g., every hour) and uploads all data from the internal database to the *Lifelog Aggregator*.

The *Lifelog Aggregator* is made of two services:

1. The *Fittracker* is responsible for accessing the *Fitbit* server and fetching data from there (see Fig. 2(b)). It is based on a Java client library that facilitates the *Fitbit* authorization and resource access. As soon as new user's data is uploaded to the *Fitbit* server, a notification is sent to the *Lifelog Aggregator*, which starts the *Fittracker* service. Then, the *Fittracker* downloads the new data using the *Fitbit* API, invoked by the Java client library.
2. The second component of the *Lifelog Aggregator* provides REST web services with JSON responses. The services enable data storage and data retrieval to/from the *Lifelog Database*. The web services accept client requests, fetch or store data from the *Lifelog Database* and returns JSON responses. There are two types of web services: base data services are used to query/update low-level life-log data from the *Lifelog Database*; high-level data services are used to query the system for the values of QoL indicators.

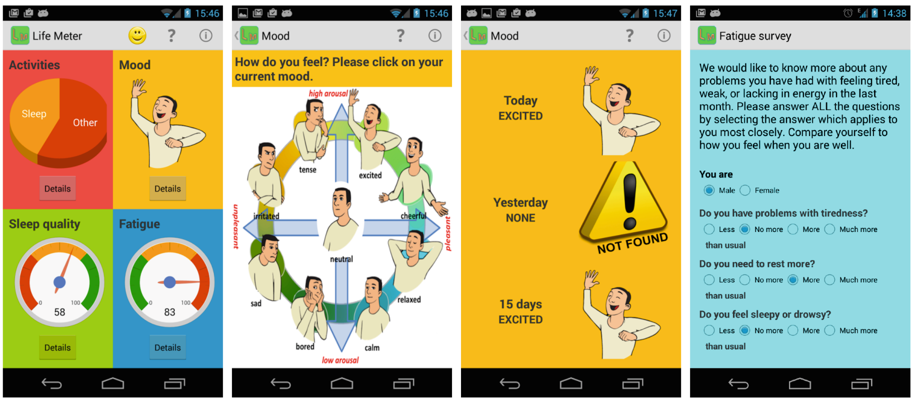
4 Quality of Life Indicators

We now illustrate *Life Meter*, an *Android* mobile application developed on top of the infrastructure illustrated above. *Life Meter* helps users raise awareness of their QoL by showing them four specific indicators: *activities* performed; *sleep* quality; level of *fatigue*; and *mood.* In healthcare, the assessment of the QoL is extremely important to measure how a disease, disability, or disorder affects an individual's well-being over time [18]. The home screen of *Life Meter* (Fig. 3(a)) shows the values of the four indicators for today.

4.1 Mood

When their mood changes, the users can use the mood input tool, accessible by clicking on the smile icon in the home screen. The mood input tool is shown in Fig. 3(b). Users can express their mood using *Pick-A-Mood (PAM)* [15], a mood reporting and visualization tool, based on the circumplex model of affect [24]. The evaluation of *PAM* demonstrated that the use of cartoon characters enables people to unambiguously and visually report their mood in a rich and easy-to-use way. *PAM* consists of three characters (a man, a woman, and a robot) that are used to personalize the pictorial representations of the mood according to the gender of the user. The robot figure is used when the user prefers not to input the gender. Users can touch the point of the screen that corresponds to how they feel in that moment. The pictures help the users report typical moods of four main categories: energized-pleasant (*excited* and *cheerful*), energized-unpleasant (*irritated* and *tense*), calm-pleasant (*relaxed* and *calm*), and calm-unpleasant (*bored* and *sad*). In addition, there is a picture for *neutral* mood.

When users click below the mood picture in the *Life Meter* home screen, the view in Fig. 3(c) is opened. The interface shows, using again *PAM*, the mood



(a) (b) (c) (d)

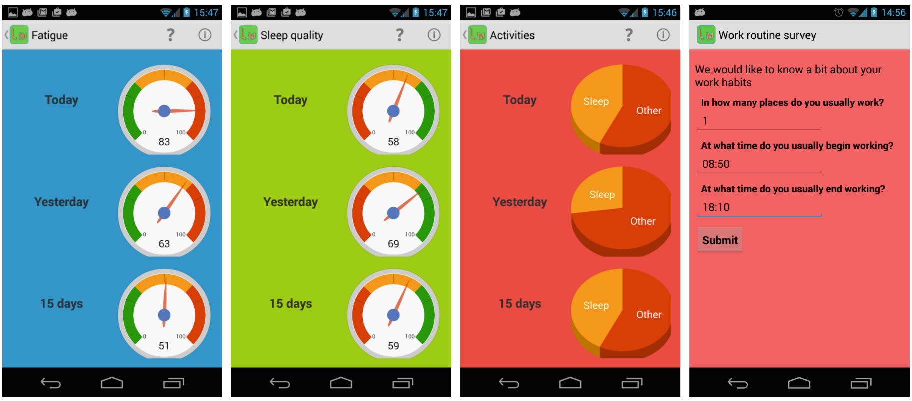
Fig. 3. Home (a), mood input (b), mood output (c), and Chalder Fatigue Scale (d).

average value for today, yesterday, and over the last 15 days (or less if there is not enough data). In the calculation of the average, every mood is weighed by the time the user persisted in that mood. When the calculation of the average mood is not possible, because of lack of user input, a special exclamation mark icon is shown. For example, in Fig. 3(c), yesterday's average is not available.

4.2 Fatigue

Fatigue is a feeling of tiredness that can have physical or mental causes. Studies report a relation between fatigue and heart rate [26]. We experimented three fatigue indicators based on heart rate variability and two derived from simple heart rate. Heart rate variability is generally considered to be better correlated with fatigue over time, but *Fitbit* trackers are not precise enough to permit an accurate calculation of it. Therefore, we decided to use the resting heart rate directly measured by the *Fitbit* tracker as input value for calculating the fatigue indicator, measured as a number in the range $[0, 100]$.

In order to set up the initial value for the indicator when users start using *Life Meter*, the *Chalder Fatigue Scale* [10] is used to acquire their initial fatigue (see Fig. 3(d)). This survey has been selected because it allows the measurement of both dimensions (physical and mental) of fatigue, it is easy to administer (there are only 11 questions) and it has been validated for the general population. The survey is administered only once, when the users access *Life Meter* for the first time, and returns their fatigue values, in a range from 0 to 11. The values are rescaled in the $[0, 100]$ interval. Since the system also knows the value of the resting heart rate at the time when the *Chalder Fatigue Scale* is administered, this resting heart rate is associated to the measured fatigue. Assuming that the fatigue indicator varies linearly with the resting heart rate, we also need to define



(a) (b) (c) (d)

Fig. 4. Fatigue output (a), sleep quality output (b), activities output (c), and work habits survey (d).

the range for this variation and therefore to set up the heart rate corresponding to the minimum (0) and maximum (100) values for the fatigue indicator. In this set up, we assume that the resting heart rate has a variation range of 12 bpm, value that is derived from literature and from empirical measurement on some subjects.

When a user clicks below the fatigue chart in the *Life Meter* home screen, the view in Fig. 4(a) is opened. The interface shows the value of fatigue for today, yesterday, and over the last 15 days (or less if there is not enough data). Today's and yesterday's values are directly derived from today's and yesterday's resting heart rates and are proportional (on a scale from 0 to 100) to the differences between the user's resting heart rates and the heart rate corresponding to the minimum fatigue.

4.3 Sleep Quality

When users click below the sleep quality chart in the *Life Meter* home screen, the view in Fig. 4(b) is opened. The interface shows the average quality of sleep for today, yesterday, and over the last 15 days (or less if there is not enough data). We use the sleep quality indicator provided by *Fitbit* to estimate the sleep quality. This indicator, in the range $[0, 100]$, is the proportion of user's "deep" sleep (sleep without movements) over the total time the user spent in bed. We calculate the average sleep quality over a reference period by averaging the quality of the sleeps in that period. Each sleep quality is weighted by the duration of the sleep.

4.4 Activities

When a user clicks below the activities pie chart in the *Life Meter* home screen, the view in Fig. 4(c) is opened. From top to bottom, the three pie charts show the amount of time the user spent today, yesterday, and on average in the last 15 days (or less if there is not enough data) doing various types of activities. Three types of activity are shown: *Work*, *Sleep*, and *Other*. The time spent for work is calculated as follows:

1. The time stamped positions of the user during the day are clustered using *Expectation Maximization Clustering* [19], which performs optimization of the number of clusters; each cluster corresponds to a specific area the user visited during the day.
2. If the number of clusters in the time window indicated by the user as "usual" work period is the same as the number of "usual" work places indicated by the user, the working time is calculated as the difference between the max and min timestamps of positions belonging to the working clusters; otherwise, no working time is detected for the day.

The sleeping time is calculated by the *Fitbit* tracker. The time for other activities is calculated by subtracting the work time and the sleeping time from the total observed time. The average time spent every day working, sleeping, or doing other activities in the last 15 days is calculated by averaging the corresponding daily times. A simple survey (Fig. 4(d)) is used to acquire the users' work habits the first time they use *Life Meter*. The data acquired in this survey is used by the activity inference algorithm described above.

5 Life Meter Evaluation

We evaluated *Life Meter* using the *Mobile App Rating Scale (MARS)* [28], a new tool specifically designed for assessing the quality of health mobile applications. The quality dimensions included in *MARS* have been selected by a panel of experts after examining and clustering criteria proposed for assessing mobile healthcare applications by several authors. Among the dimensions, we decided to evaluate *functionality, aesthetic*, and *subjective quality* of *Life Meter*. Functionality and aesthetic refer to two fundamental aspects of mobile applications: being suited to serve their purpose well; and having an attractive GUI design. Subjective quality summarizes items as if the users would recommend the app to others, how frequently they would use the app in the future, or the overall star rating. We compared *Life Meter* with a benchmark obtained by evaluating 50 health mobile applications with the MARS tool.

We involved in the experiment 10 subjects (5 female, 5 male) recruited using convenience sampling [9] among researchers and students of our university and among our acquaintances. We adopted convenience sampling to be able to quickly run the experiment and draw conclusions on the *Life Meter* prototype. In order to mitigate the well known drawbacks of the sampling method, we payed attention that the sample was gender-balanced and included people with heterogeneous experience with mobile devices and wearable trackers. Two subjects had problems installing the system on their smartphones and drop the experiment[1], while 8 subjects completed it. The subjects registered on the *Fitbit* website and used the tracker for some days, in order to get familiar with it. In this period the tracker collected the data that was then used to initialize the QoL indicators. After some days, the subjects were informed how to download *Life Meter* from the Android marker, and how to install it on their smartphones. Then, they used *Life Meter* for about 15 days, in conjunction with the *Fitbit* tracker. At the end of the two weeks, the subjects were asked to fill in an online *MARS* survey.

The average rate given by the group of users to *Life Meter* functionality was 4.57 (max is 5), while the average functionality of the benchmark is 4.01. The functionality of *Life Meter* resulted to be significantly better than the benchmark (t-test, $p < 0.01$). The average rate of *Life Meter* aesthetic was 3.29, while the average aesthetic of the benchmark is 3.49. In this case, *Life Meter* underperformed the benchmark. The average rate of *Life Meter* subjective quality was 3.07, and resulted to be significantly better than the benchmark, which scores

[1] One had a too old version of Android and the other was not able to successfully follow the app installation instructions.

2.19 (t-test, $p < 0.01$). In summary, *Life Meter* demonstrated to outperform a benchmark composed by mobile health applications available on the market on two dimensions out of three. The reason for the inferior performance on aesthetic can be due to the fact that *Life Meter* is still a prototype and, at that point, the optimization of the look and feel was not a major priority.

In addition to rating the above quality dimensions, we measured the perceived impact of *Life Meter* on users' awareness of their QoL, their knowledge/understanding of it, and their inclination to improve it. We asked the users to judge if "Life Meter is likely to increase awareness of the importance of monitoring QoL indicators" and we obtained a score of 4.13 on a scale from 1 to 5. We obtained the same evaluation for the statement "Life Meter is likely to increase knowledge/understanding of QoL indicators", while the users agreed less (3.25) with the statement "Life Meter is likely to change attitudes toward improving QoL". These results indicate that *Life Meter* can be useful for rising the awareness of the users about the necessity of monitoring their QoL and can help them better understand the meaning of QoL indicators. As expected, users are less convinced that *Life Meter* can successfully support a life change that improves the users' QoL, probably because the current version of the system does not have any advisory functionality.

6 Conclusions

In this paper, we have presented a comprehensive system able to monitor the users' daily activity, build life-logs integrating data from multiple sources (wearable trackers, smartphone sensors, and manual input), calculate high-level QoL indicators from the life-logs, and show the indicators to the users via a dedicated mobile application. The system focuses on deriving high-level summaries from heterogeneous data, while other important aspects needed by a comprehensive life-logging framework, namely, long-term data preservation and privacy, are left as future work. The evaluation we performed demonstrated that our system is a solid starting point for the implementation of proactive advisory systems (able to take the initiative and propose information and advice) dedicated to various aspects of health care and well-being. In the future, we intend to integrate the system with *Smart Allergy Taming* [23] (a system supporting allergic patients to better manage their immunotherapy) in order to automatically provide indicators that help patients assess the efficacy of their therapy. Moreover, we also plan to exploit the developed infrastructure with *ChefPad* [17], a food recommender system that not only offers recipe recommendations that suit users' taste, but it also takes the users' health into account.

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