Wisdom of the IoT Crowd: Envisioning a Smart Home-based Nutritional Intake Monitoring System

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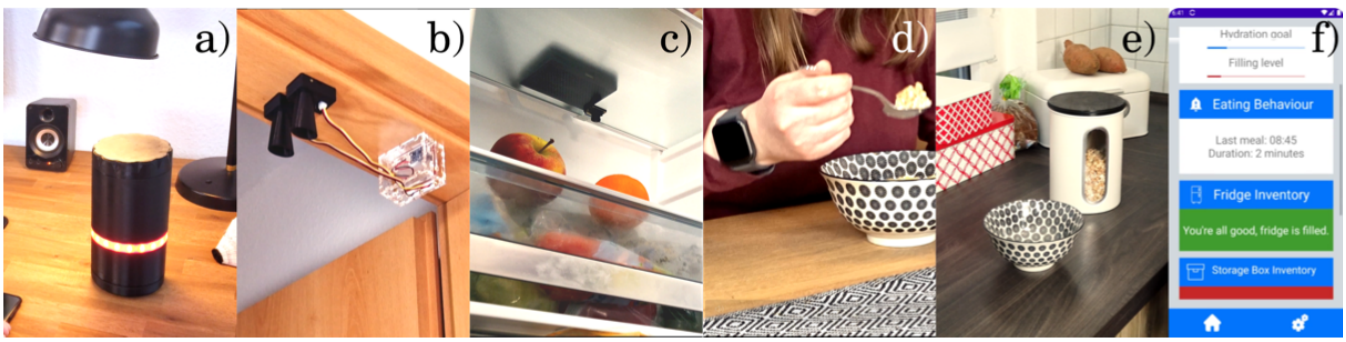

Figure 1: We present "Wisdom of the IoT Crowd" a smart home-based nutrition intake monitoring system that consists of (a) a smart bottle tracking the drinking behavior, (b) an indoor position and activity tracking module, (c) a smart fridge that keeps track of the fridge inventory, (d) a food intake monitoring module that detects eating motions, and (e) a smart storage box that monitors food stocks. (f) The collected information is used to generate recommendations presented in our Android App.

ABSTRACT

Obesity and overweight are two factors linked to various health problems that lead to death in the long run. Technological advancements have granted the chance to create smart interventions. These interventions could be operated by the Internet of Things (IoT) that connects different smart home and wearable devices, providing a large pool of data. In this work, we use IoT with different technologies to present an exemplary nutrition monitoring intake system. This system integrates the input from various devices to understand the users' behavior better and provide recommendations accordingly. Furthermore, we report on a preliminary evaluation through semi-structured interviews with six participants. Their feedback highlights the system's opportunities and challenges.

CCS CONCEPTS

• **Applied computing** → *Health care information systems*; • **Human-centered computing** → *Interaction devices*; **Human computer interaction (HCI)**.

KEYWORDS

internet of things, smart home, nutrition monitoring, health

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1 INTRODUCTION

According to the World Health Organisation (WHO), four million people die each year as a result of obesity and overweight[1]. The WHO further reported that the number of overweight and obese has been increasing since the last decade. Between 1975 and 2016, the number is tripled. Thus, there is a higher urge to find long-term effective solutions that could not only reduce the phenomenon but also prevent the cause and influence peoples' lifestyles [10]. Witkos et al. [41] sees the main reason for obesity as the imbalance of the calories taken in comparison to the exerted energy. Therefore, technical solutions and research have been focusing on providing tools that could help users to keep track of the nutrition intake (e.g., [22, 35, 40]) and the level of executed activity (e.g., level [3, 6]). While these solutions have been proven useful and effective to monitor nutrition intake for the enthusiastic test-groups, the interest of using new applications declines over time [15], as users forget to monitor their food or do not like the effort that comes with it.

In recent years, smart homes gained popularity, allowing users to automate their homes. These smart home devices are often equipped with different sensors to collect data on users for their intended purpose. In this work, we propose using smart home devices as a ubiquitous in-home nutrition monitoring system.

Inspired by previous research, we developed five different IoT modules that help to monitor specific aspects of users' nutritional intake (see Figure 1). The first module is a smart bottle that can communicate the amount as well as the type of consumed liquid. The second one is used for indoor positioning to indicate the frequently used places and the user's activity level. The third one is an in-fridge smart camera that detects the types of food stored by the user. The fourth is a smart storage box that communicates the amount of consumed stored substance. The last used module is a smartwatch to monitor hand motion while eating.

In this paper, we first describe the design and development of our nutritional intake monitoring system. Then, we present interviews with six participants to get qualitative insights on our envisioned system. During the interviews, we showed the participants a video of our system in action to adapt to the current pandemic situation. Our findings show that participants see potential in integrating the system into their life as it requires only initial effort (setup) and could be used for different purposes. Nevertheless, some indicated concerns regarding data privacy.

Our contribution is twofold: (1) exemplary system that demonstrates the potential of connected IoT devices for monitoring nutritional intake, and (2) preliminary feedback from six users that highlight the opportunities, challenges as well as potential improvements of the system.

2 SMART HOME-BASED NUTRITIONAL INTAKE MONITORING SYSTEM

We envision a system that monitors users' nutritional intake via integrating different sensing modules called *Wisdom of the IoT Crowd* (see Figure 2). We thereby utilize existing wearable and smart home devices as well as additional IoT devices that we all integrate as modules into our system. The data from these modules is collected in a hub which in return is aggregated in a data center that communicates to an android application. The modules deployed in the system are used for data collection that keeps track of food stocks, eating and drinking behavior, as well as the physical activity of the user. While implementing a nutrition monitoring system has been proposed in previous work (e.g., [18, 36, 37]), this is the first work to propose a holistic approach of such a nutrition monitoring system.

2.1 HUB and Data Center

To be able to send the data from various devices into a single platform, we collect it via a HUB, which would be installed in the users house and communicates with the different modules over various communication channels (e.g., TCP sockets, REST, MQTT). It serves as a middleware that translate the vendor specific interface with a general interface based on the devices capabilities as an abstraction level (e.g., a smart watch tracking eating motions can be easily substituted by another smart watch from a different company or even by a camera based system detecting eating motions). The HUB is then connected to a data center, which is implemented as a cloud that also communicates with the HUB over TCP. In the data center, the data is then aggregated and interpreted to generate recommendations for users. Since the input from each sensing module reflects only a certain aspect (e.g., food or drink intake), combining multiple inputs allows a more holistic view on user' behaviour and, thus, offers new potentials for the gathered data.

2.2 Internet of Things Modules

In total, we developed five different modules based on previous work. We envision that such devices will be common in the future similar to smart light bulbs getting more and more common nowadays.

2.2.1 Smart bottle module. An important aspect of nutrition monitoring is the users' fluid intake. One approach is to monitor the drinking vessels [8, 12, 19], which could reach a detection precision of 99% [8] of the drinking movement or 85% for drinking volume based on the movements [13]. Some products use float sensors to measure the level of fluid inside a vessel [2] or by using weight measurement to identify the volume change [3]. Overall, the direct weight measurement led to an accuracy of 97% [4]. Further research did not only focus on the quantity of taken fluid but also the quality. To classify the different types of liquids, research used a capacitor and a coil to measure the viscosity and dielectric properties of liquids [20]. Other approaches used a radar-based technology to classify materials including transparent ones [45] or optical, ion-selective electrical pH, and conductivity sensors [26]. Therefore, based on previous research [25], we implemented a smart bottle where we measure the fluid volume by weighing it (cf., Figure 1 – a). For the fluid classification a spectrometer setup is used similar to the smartphone-based approaches [17, 46], where we mounted a LED strip around the bottle and measured the reflected light using color sensor. In our system, the smart bottle module is responsible for

[1] World Health Organisation (WHO). https://www.who.int/health-topics/obesity, last retrieved July 15, 2021.

[2] https://hidratespark.com/, https://www.thermos.com/smartlid

[3] https://hidratespark.com/products/hidratespark-steel

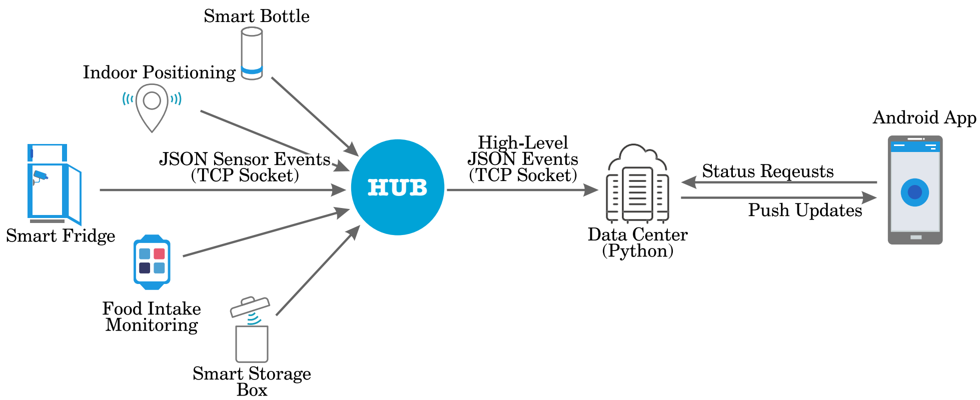

Figure 2: Integrating the output data from several IoT modules to reflect on the users' nutrition behaviour in home.

tracking the type and amount of consumed fluid. This information would be used to remind the user to drink enough.

2.2.2 Indoor positioning module. To define human activity, we link the activity to the place where the user is. For example, as input, we can sense that the user entered the kitchen, opened the sweets box and started eating. As a conclusion, the user ate sweets. Localisation could be done by various different sensors. Since we aim to localize users, we opted for proximity sensors allowing us to understand the users location on a room level [23, 38].For that we use passive infrared sensors (PIR) to detect the users' motion in certain locations as suggested in previous work [16, 24, 30, 34, 47], which we integrated on the door frame (cf., Figure 1 – b).

2.2.3 Smart fridge module. Previous research proposed using image processing to analyze the quantity and the type of the consumed food from meal images [29, 42]. Various deep learning algorithms have been implemented and explored for this purpose [21, 27, 43]. In our work, we use images captured by a camera that we placed inside a fridge to capture both objects and barcodes of food items placed in it (cf., Figure 1 – c). For object detection, we used Single Shot MultiBox Detector (SSD) neural network that could be used in runtime detection [28] along with MobileNet [33] that combined can result in very high performance with little computing power [2].

2.2.4 Smart storage box module. We implemented a smart storage box (cf., Figure 2), that can reflect on the amount of the used content by measuring how much content still remains in the box using ultrasonic sensors similar to the work of Premgi [31] or Fisher [11]. The smart box is enhanced by a magnetic switch that indicates whether the box is opened or not. Along with the use of data from the ultrasonic sensor mounted on the box cover, the amount and the frequency of access to the content are detected. This data is used to monitor how much of specific content the user ate and report on the excess use or the shortage of it.

2.2.5 Food-intake monitoring module. Many of the work focus on using unobtrusive sensors and low-cost solutions to monitor eating gestures. Measuring food intake through inertial sensors has been studied in literature [1]. Particularly placing such sensors on the wrist allows a good tracking of eating motions [9, 32] which researchers also achieved using smartwatches [9, 48]. Therefore, to monitor the users eating behaviour, we use a smart watchs inertial sensor to monitor the eating movements. We applied that by cutting down the eating gesture using thresholds to identify picking up food reaching the mouth and from the mouth downwards. In our work, the food-intake module is reflecting the number of bits the users had. This data would be integrated with the other modules to specify the quantity consumed of certain food. Further, the integration of different modules allows us to improve the accuracy since we can predict the likelihood of eating (e.g., by being in the kitchen and opening a smart storage box beforehand).

2.3 Android Application

We developed an android application that allows the users to control the system as well as receive information on their current performance such as daily and weekly summaries of their nutrition intake, notification on their eating and drinking behavior, storage box and fridge inventory, and daily goals. In an initial step, the users indicate basic information such as sleeping range (i.e., from when till when), the maximum and minimum expected calorie intake, the expected amount of fluid intake, and what should the fridge as well as the smart storage box contain. This information is then used in the data center to trigger notifications if the users do deviate from the goals (e.g., too little fluid intake).

Notifications. Overall we designed 11 types of notifications that we categorized into three groups. **(1) Consumption dependent**: In this group the notifications from the smart bottle indicates if the filling level is less than 85%, or the detected drinking amount is 25% behind the drinking goal or if the user is drinking unhealthy drinks. Also, this group has the notifications triggered from both the smart storage box and the smart fridge if they are not properly closed or if there is something missing from the pre-defined inventory objects. **(2) Context dependent**: This includes the notifications reflecting a wrong behavior related for example to the food intake and the user position (e.g., standing in the kitchen to have a quick snack and not granting enough time for the dining table to eat a proper meal).

(3) Time dependent: This includes the notifications retrieved in a certain time interval of a day (e.g., when the system detects the user eating in the sleeping hours).

3 EVALUATION

Due to the ongoing corona pandemic, we decided to conduct online semi-structured interviews to evaluate the overall idea of the *Wisdom of the IoT Crowd* system. Since participants could not experience the system hands-on, we present the system in form of a video that demonstrates all components and the system in action[4].

3.1 Interview Design

We based our questions on the relevant entities retrieved from proposed user acceptance models [7, 14, 39, 44] and categorised our questions into four main categories. The first category is the use, which is linked to the facilitating conditions and effort expectancy. The second category is trust with which perceived adaptivity, social presence (i.e., to which extent the user would be noticed while using the technology) ,and perceived sociability (i.e., to which extent the technology would affect the users' relationship with the society) are associated. The third category is the perceived value, which is linked to the social value (i.e., willingness to use the technology with others), hedonic value, utilitarian, visual attractiveness, functionality, and compatibility. The last category of questions reflects the users' technical affinity.

3.2 Participants and Procedure

Overall, six participants took part in the semi-structured interview (3 female, 3 male $M = 26.2$, $SD = 3.1$). The average duration was about 40 minutes. We conducted the study via video conference, which we recorded upon obtaining consent from each participant. After welcoming each participant at the beginning, we collected the demographic (i.e, gender and age). Following that, we showed them a video of how the different components of the system work and envisioned use cases. After we confirmed with the users that they understood the concept and started the interview.

3.3 Results and Discussion

We transcribed all six semi-structured interviews. Afterward, we conducted a semantic inductive thematic analysis (as described by Braun and Clarke [5]). In our analysis, two researchers independently went through the coding process and formed an individual list of themes ,and consolidated them at the end. Overall, this resulted in five themes with 37 codes. Following, we present each theme and highlight the main outcomes.

Motivation. The participants indicated the different motivating aspects that would encourage them to use the system. The first main reason was having a multipurpose system that would not be monitoring *"only nutrition but also daily habits"(P5)* and more aspects of their *"life"(P6)*. Others indicated that they would like to have a system with *"more potential analysis"*(P1), as P4 further elaborated *"I want to have a smart home system in which all functions are in...not 10 different systems with 10 different providers"*. P2 and P3 provided examples of having an auto-generated shopping list and healthy recipes based on the fridge content. This indicates that users want to repurpose existing smart home components for such a system and similarly repurpose the modules provided here for other applications. Thus, the idea of having a similar concept to the application stores known from mobiles can be beneficial for smart homes as well.

Functionality. The participants mostly commented on the *providing reminders* feature that the system communicates either for monitoring food and drinks intake or activity level. The participants further elaborated on other features that they would like to have. Participants started by being generic requiring *"clever solutions that would just save time"*(P6) and do not require *"manual data entry"*(P2). Others wanted more of *"life-style changing system .. to achieve certain goals"*(P5) that is *"personally-tailored"*P5. P1 further elaborated that she wanted a system that would detect and adapt to her living pattern by saying *"now I kind of have my period and that's why I have cravings"*. This shows that users see the need to personalize the system and allow them to define their own goals and exceptions.

Further features requested by the participants included physiological monitoring to *"track sports"*(P3) through *"pulse measuring"*(P5) and *"steps count"*(P2) or if one had enough sleep as indicated by P6. Thus, the scalability of the system is important which is covered by the hub approach used in our system. This allows us to include various components the users have in their homes automatically.

Design. The participants indicated their concerns as well as potential improvements in the design of the system, both for front and back ends. The main challenge that all the participants highlighted and reflected on was data protection and privacy. Through the interview we wanted to get more insights into whether a big known company name would affect their concern however that had no influence on their concerns as P2 described *"even in a small scale, I find it personally difficult to build up trust, but if it is clear where we are going ... and how the data is stored or accessed"*. P6 further elaborated *"there is always the problem with the smart home devices... because it is now just somehow a recording of our daily life"*. P4 provided an example of data misuse saying *"if I have a car accident and look, the system indicated that I had a high level of sugar in the blood and was not quite receptive, so the insurance does not pay"*. This indicates that such a system needs to build up trust and respect the users privacy.

Envisioned Ease of Use. All participants highlighted that the system is easy to use. For example, P2 mentioned: *"the system is so simple because once installed, it runs"* and one does not *"have to maintain it"*(P3). P5 claims that the only effort that is linked to using the system is following the recommendations of the system and therefore *"change habits"* (e.g., drinking more water). Similarly, users valued the systems automatism. For example, P4 said: *I do not have to do much* and P2 added that *"the IoT system will do it for you"*. Thus, the overall idea of sensing information implicitly through the modules seems to be promising and a benefit of the system.

Social. Concerning the social aspects, P3 draws an analogy to sports applications on smartphones. While he argues that sharing

[4]The video is attached as auxiliary material to this submission and will be published with it.

information in sports applications has a benefit towards the motivation, he does not see the same benefit in the nutrition monitoring system as he says: *"I do not see the benefit of telling my friends, I now have nine bottles of beer in the fridge"*. However, other aspects might be worth sharing. Both P5 and P6 mentioned their willingness of sharing the system with others if it has any positive impact. For example when the user aims at losing weight, sharing that a snack attack is currently happening might trigger a response from the friends that might stop such unhealthy behavior. Nevertheless, it is important to understand what aspects users want to share and allow them to have fine-grained control on which information is kept private.

3.4 Limitations and future work

We acknowledge the following limitation to our work. Our study focused only on highlighting the potentials of the system based on only qualitative feedback. Therefore, we recommend that in the future the findings are addressed and tested in real life. Furthermore, the design of the communicated notifications should be investigated. As in our system, the notifications reflect on wrong behaviour, this might negatively affect the user's mental health by triggering feelings of guilt.

4 CONCLUSION

In this paper, we presented our vision of a smart home nutrition monitoring system. Our system integrates the data from five different sensing modules, namely a smart bottle, indoor positioning, smart fridge, food intake monitoring, and a smart storage box. The system uses the collected data to form a holistic overview of the user's nutrition intake behaviour and provides recommendations accordingly. Furthermore, we conducted a preliminary evaluation to explore the opportunities and the challenges facing such smart monitoring systems. We particularly identified important aspects that need to be considered when designing nutrition monitoring systems based on smart home devices such as repurposing of existing devices, privacy, implicit data collection, and including appropriate social capabilities.

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