Reflecting on Approaches to Monitor User's Dietary Intake

Jonas Keppel
Human-Computer Interaction Group,
University of Duisburg-Essen
Essen, Germany
jonas.keppel@uni-due.de

Uwe Gruenefeld
Human-Computer Interaction Group,
University of Duisburg-Essen
Essen, Germany
uwe.gruenefeld@uni-due.de

Marvin Strauss
Human-Computer Interaction Group,
University of Duisburg-Essen
Essen, Germany
marvin.strauss@uni-due.de

Luis Ignacio Lopera Gonzalez
Chair of Digital Health,
Friedrich-Alexander University
Erlangen, Germany
luis.i.lopera@fau.de

Oliver Amft
Chair of Digital Health,
Friedrich-Alexander University
Erlangen, Germany
oliver.amft@fau.de

Stefan Schneegass
Human-Computer Interaction Group,
University of Duisburg-Essen
Essen, Germany
stefan.schneegass@uni-due.de

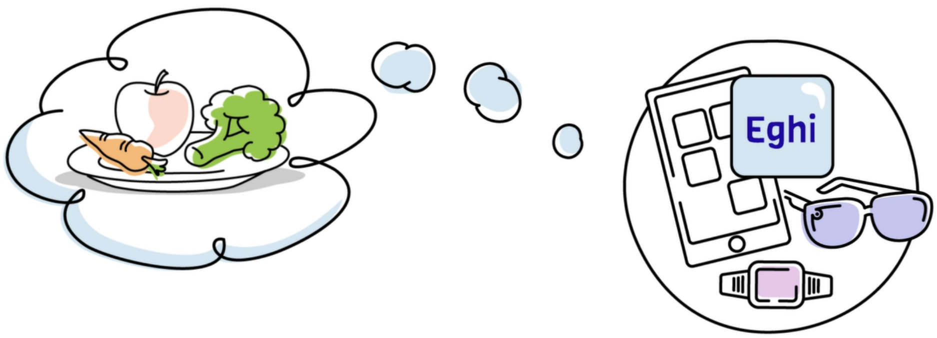

Figure 1: Providing user recommendations for healthier dietary behavior requires monitoring dietary intake. Therefore, in previous work, researchers have proposed different approaches that utilize the user's smart devices (e.g., smartphones, smartwatches or smartglasses).

ABSTRACT

Monitoring dietary intake is essential to providing user feedback and achieving a healthier lifestyle. In the past, different approaches for monitoring dietary behavior have been proposed. In this position paper, we first present an overview of the state-of-the-art techniques grouped by image- and sensor-based approaches. After that, we introduce a case study in which we present a Wizard-of-Oz approach as an alternative and non-automatic monitoring method.

CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**; **Ubiquitous and mobile computing**; • **Applied computing** → *Consumer health*; *Health informatics.*

KEYWORDS

eHealth, behavior change, nutritional intake, dietary behavior

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
MobileHCI 2022, September 28–October 1, 2022, Vancouver, Canada
© 2022 Association for Computing Machinery.

ACM Reference Format:
Jonas Keppel, Uwe Gruenefeld, Marvin Strauss, Luis Ignacio Lopera Gonzalez, Oliver Amft, and Stefan Schneegass. 2022. Reflecting on Approaches to Monitor User's Dietary Intake. *A position paper submitted to "Utilizing Interactive Technologies for Encouraging Healthy Dietary Behavior" workshop held at the ACM International Conference on Mobile Human-Computer Interaction (MobileHCI 2022).*

1 INTRODUCTION

According to the World Health Organization [30], obesity has nearly tripled worldwide in the last 45 years. In 2016, 39% of all adults were overweight, while even 13% were obese. Moreover, the prevalence of obesity is increasing among children and adolescents. While in 2000, only 2.9% of all 5 to 19-year-olds were obese, in 2016, 6.8% of this group suffered from obesity [31]. Especially in the regions of Europe and North America, people suffer from unhealthy lifestyles that lead to obesity [13]. The observed trend will profoundly impact the health of our society, as overweight and obesity can lead to diseases such as cardiovascular disease, diabetes, and cancer [7, 20, 23].

Besides physical activity, the most important factor for a healthy lifestyle is the dietary behavior [22]. To estimate a person's current health status, to predict the health impact due to behavioral changes, and to provide helpful recommendations to motivate such changes, the person's dietary behavior is required. To capture dietary behavior automatically, several food intake parameters are required, such as time of day, duration, type of food, quantities, calories, nutritional values, fluid intake, among others. However, these parameters vary in capture difficulty. For instance, different parameters may require different sensors and devices, or in some parts, we have no solution to monitor them efficiently (or at all) [2, 6, 19, 26].

In this position paper, we first discuss previous work on monitoring dietary intake. Here, we distinguish between image- and sensor-based analysis and provide an overview of state-of-the-art approaches, highlighting their individual strength and weaknesses. Thereafter, we introduce the EGhI project[1] as a case study for dietary monitoring and discuss the approach we plan to apply.

2 DIETARY MONITORING APPROACHES

Detailed self-reports, called diaries, were originally used to record food intake, as these initially represent a straightforward way for any user to document their daily food intake [9]. However, these diaries usually contain a high bias and are unsuitable for longer use, as the user's motivation decreases after a few days. Usually values are estimated for the sake of simplicity, copied from the previous day, or the documentation is aborted and very rough estimates are made at the end of the week. Especially, the users' awareness for food intake with regards to snacking is very limited retrospectively [29] and, therefore, the estimated amount of food intake can be off by 50% in either direction [27]. Therefore, automatic dietary monitoring is desirable to enable reliable long-term recording of food intake. Typical approaches are image-based [37], which are enabled by the progress in computer vision using convolutional neural networks. But also sensor-based approaches have been studied [6].

2.1 Image-based Analysis

Since it is convenient, the initial ideas for image-based monitoring of dietary behavior are using cameras of wearables such as smart glasses [25] or smart phones [37]. Object detection and classification can be used to detect dietary intake using artificial intelligence, particularly convolutional neural networks. By training with food databases such as the Pittsburgh fast-food image dataset (PFID) [12] or the Food-101 [8], detection of food intake and thus detection of time and duration can be logged. However, accurate estimation of calories and nutritional values is difficult, as even recognizing specific food categories can be problematic. Some ingredients are difficult to distinguish after cooking when the food is processed [11]. Estimating portion sizes is also challenging because no scale is initially given. This can be made possible by using reference objects, but these must then always be carried along [14, 37]. To improve usability, a suitable reference object can be selected such as normalized plates, cutlery, or for example, the user's thumb [24]. Alternatively, the reference object such as a cube can be displayed in augmented reality [33]. However, most of the image-based approaches still require the user to actively take photos including the reference object. Therefore, the disadvantage of of users forgetting to log some of their food, especially snacks, is still comparable to paper-based reports [34].

[1] EGhI project. https://www.eghi-projekt.de/, last retrieved July 22, 2022.

2.2 Sensor-based Analysis

To actually perform automated monitoring and thus minimize reporting errors, researchers have been working on on-body sensing of eating behavior. The data of used sensors can resemble some self report information [6] while logging the data continuously and location-independent. For this research area, different types of sensors and attachment points are used to log food intake: First, arm movements while eating and thus intake gestures can be detected using wristbands with IMUs [18]. Chewing then produces sounds that can be recorded, for example, with a wearable such as ear attached microphones [3] or smart glasses [28]. Different textures of food result in different chewing sounds and, therefore, it is possible to classify the chewed food or at least the type of food [4]. Swallowing then also produces sounds, but the throat movement can also be detected. This can be used to identify the volume of food intake [5]. In addition, other methods can be used: A cardiac response such as heart rate and blood pressure change takes place and there is a temperature increase after food intake [15]. Stomach sounds of gastric activity can also be detected [32]. Furthermore, there is also a change in body weight and composition, which can be measured with an external scale. However, when trying to design a more convenient and mobile system, accuracy is a challenge [16].

Another major approach for dietary monitoring is the usage of sensor-based utensils and tables. Smart dining table approaches are location-dependent by design but can be used to recognize the plates where food is taken from via RFID tags [10]. By tracking the weight change, the system can predict the quantity of food intake. Using a fine grained pressure textile matrix, such systems have been made more mobile [36]. Additionally to tracking the weight change and identifying the plate that is used, food intake actions, such as cutting, scooping, and stirring can be detected. Prior work regarding smart utensils also presented mobile approaches to perform automated monitoring. For example, smart forks can detect food pick-up gestures and estimate the food amount that is consumed [35], while a smart spoon analyzing the reflected light spectra of an LED array can recognize the meal composition of food on top of the utensil [17]. Similarly, smart cups with optical spectrometers, pH and conductivity sensors can classify liquid intake [21]. All in all, no single approach can cover all dimensions of dietary behavior. Therefore, the question remains to what extent a combination of these approaches together with image-based analysis can provide comprehensive monitoring.

3 CASE STUDY: EGHI PROJECT

Our work is embedded in the EGhI project, which aims to develop an AI-based assistance system that supports healthy everyday behavior. Wearables such as smartphones and smartwatches will be used as data sources, while other sensing devices may supplement these depending on the parameters selected for monitoring (e.g., a sensor batch with a thermal camera to monitor drinking and food intake [1]). The goal is to model user behavior and derive recommendations for healthier lifestyle choices. Nevertheless, it remains unclear which recommendations we can provide as our model heavily depends upon the measured parameters. While we could directly start to develop measuring techniques for different devices, the contribution of the different parameters to the model

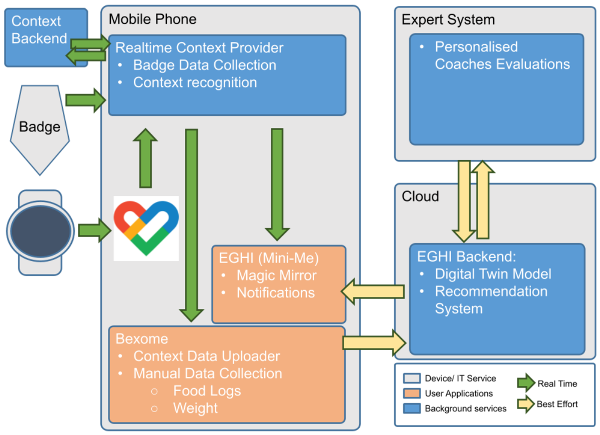

Figure 2: Proposed Architecture for the EGhI project

may vary (and building functional prototypes is time-consuming). Hence, we plan to take a Wizard-of-Oz approach in our initial field studies with the duration of multiple weeks. The fundamental idea is that participants are asked to take photos of their food intake in their daily lives and to record – automatically in the background – from available sensors (e.g., inertial sensors in smartphones). Thereby, we can manually inspect and label participants' dietary behavior (with the help of experts) and identify relevant parameters as well as potential ways of measuring them (e.g., one could map the smartwatch data to the type of food consumed). As a result, we can specify the parameter of our model and simulate data input with our Wizard-of-Oz data collected. Later, we can design and implement the automatic recording of specific parameters and replace the manually collected data. Following this approach, we can explore different user interfaces and ways of communicating the recommendation to users early on. Moreover, we can focus on measuring only relevant parameters for which we know that they provide a meaningful contribution to the user model. In Figure 2, we illustrate EGhI's proposed architecture to implement our Wizard-of-Oz approach. The architecture connects to an expert systems to provide overall participant guidance and recommendation evaluation. To collect the data required to detect dietary behavior patterns, the architecture uses a mobile phone with two wearable devices that collect contextual information using a context provider and the BEXOME application to collect manual entries. The EGhI back-end processes the collected data using a Digital Twin model to generate behavioral changes recommendations that are delivered to the user using state of the art HCI applications, like smart notifiers, or research prototypes such as a magic-mirror. The latter is intended to make dietary choices and their long-term effects clear to users ahead of time.

ACKNOWLEDGMENTS

This work is partially funded by the German Federal Ministry of Education and Research (16SV8528).

REFERENCES

[1] Rawan Alharbi, Chunlin Feng, Sougata Sen, Jayalakshmi Jain, Josiah Hester, and Nabil Alshurafa. 2021. *HeatSight: Wearable Low-Power Omni Thermal Sensing.* Association for Computing Machinery, New York, NY, USA, 108–112. https://doi.org/10.1145/3460421.3478811

[2] Oliver Amft. 2011. Ambient, On-Body, and Implantable Monitoring Technologies to Assess Dietary Behavior. In *Handbook of Behavior, Food and Nutrition*, Victor R. Preedy, Ronald Ross Watson, and Colin R. Martin (Eds.). Springer New York, New York, NY, 3507–3526. https://doi.org/10.1007/978-0-387-92271-3_219

[3] Oliver Amft, Mathias Stäger, Paul Lukowicz, and Gerhard Tröster. 2005. Analysis of Chewing Sounds for Dietary Monitoring. 56–72. https://doi.org/10.1007/11551201_4

[4] Oliver Amft and Gerhard Tröster. 2008. Recognition of Dietary Activity Events Using On-Body Sensors. *Artif. Intell. Med.* 42, 2 (feb 2008), 121–136. https://doi.org/10.1016/j.artmed.2007.11.007

[5] Oliver Amft and Gerhard Tröster. 2006. Methods for Detection and Classification of Normal Swallowing from Muscle Activation and Sound. *Proc. of 1st International Conference on Pervasive Computing Technologies for Healthcare*, 1–10. https://doi.org/10.1109/PCTHEALTH.2006.361624

[6] Oliver Amft and Gerhard Tröster. 2009. On-body sensing solutions for automatic dietary monitoring. *Pervasive Computing, IEEE* 8, 2 (2009), 62–70. https://doi.org/10.1109/MPRV.2009.32

[7] Franca Bianchini, Rudolf Kaaks, and Harri Vainio. 2002. Overweight, obesity, and cancer risk. *The Lancet Oncology* 3, 9 (2002), 565–574. https://doi.org/10.1016/S1470-2045(02)00849-5

[8] Lukas Bossard, Matthieu Guillaumin, and Luc Van Gool. 2014. Food-101–mining discriminative components with random forests. In *European conference on computer vision.* Springer, 446–461. https://doi.org/10.1007/978-3-319-10599-4_29

[9] Lora E. Burke, Melanie Warziski, Terry Starrett, Jina Choo, Edvin Music, Susan Sereika, Susan Stark, and Mary Ann Sevick. 2005. Self-Monitoring Dietary Intake: Current and Future Practices. *Journal of Renal Nutrition* 15, 3 (2005), 281–290. https://doi.org/10.1016/j.jrn.2005.04.002

[10] Keng-hao Chang, Shih-yen Liu, Hao-hua Chu, Jane Yung-jen Hsu, Cheryl Chen, Tung-yun Lin, Chieh-yu Chen, and Polly Huang. 2006. The Diet-Aware Dining Table: Observing Dietary Behaviors over a Tabletop Surface. In *Pervasive Computing*, Kenneth P. Fishkin, Bernt Schiele, Paddy Nixon, and Aaron Quigley (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 366–382.

[11] Jingjing Chen and Chong-wah Ngo. 2016. Deep-Based Ingredient Recognition for Cooking Recipe Retrieval. In *Proceedings of the 24th ACM International Conference on Multimedia* (Amsterdam, The Netherlands) *(MM '16)*. Association for Computing Machinery, New York, NY, USA, 32–41. https://doi.org/10.1145/2964284.2964315

[12] Mei Chen, Kapil Dhingra, Wen Wu, Lei Yang, Rahul Sukthankar, and Jie Yang. 2009. PFID: Pittsburgh fast-food image dataset. In *2009 16th IEEE International Conference on Image Processing (ICIP)*. 289–292. https://doi.org/10.1109/ICIP.2009.5413511

[13] WHO Europe. 2007. The challenge of obesity in the WHO European Region and the strategies for response. *Kopenhagen: WHO* (2007).

[14] Shaobo Fang, Chang Liu, Fengqing Zhu, Edward J. Delp, and Carol J. Boushey. 2015. Single-View Food Portion Estimation Based on Geometric Models. In *2015 IEEE International Symposium on Multimedia (ISM)*. 385–390. https://doi.org/10.1109/ISM.2015.67

[15] HR Farshchi, MA Taylor, and Ian A Macdonald. 2004. Decreased thermic effect of food after an irregular compared with a regular meal pattern in healthy lean women. *International Journal of Obesity and Related Metabolic Disorders* 28, 5 (2004), 653–660.

[16] Hongwei Hsiao, Jinhua Guan, and Matthew Weatherly. 2002. Accuracy and precision of two in-shoe pressure measurement systems. *Ergonomics* 45 (07 2002), 537–55. https://doi.org/10.1080/00140130210136963

[17] Qianyi Huang, Zhice Yang, and Qian Zhang. 2018. Smart-U: Smart Utensils Know what You Eat. In *IEEE INFOCOM 2018 - IEEE Conference on Computer Communications*. 1439–1447. https://doi.org/10.1109/INFOCOM.2018.8486266

[18] Holger Junker, Oliver Amft, Paul Lukowicz, and Gerhard Tröster. 2008. Gesture spotting with body-worn inertial sensors to detect user activities. *Pattern Recognition* 41 (06 2008), 2010–2024. https://doi.org/10.1016/j.patcog.2007.11.016

[19] David Kopyto, Lena Uhlenberg, Rui Zhang, Valeska Stonawski, Stefanie Horndasch, and Oliver Amft. 2021. AIM in Eating Disorders. In *Artificial Intelligence in Medicine* (living reference work ed.). Springer International Publishing, Cham. https://doi.org/10.1007/978-3-030-58080-3_213-1

[20] Mitchell A. Lazar. 2005. How Obesity Causes Diabetes: Not a Tall Tale. *Science* 307, 5708 (2005), 373–375. https://doi.org/10.1126/science.1104342 arXiv:https://www.science.org/doi/pdf/10.1126/science.1104342

[21] Jonathan Lester, Desney Tan, Shwetak Patel, and A.J. Bernheim Brush. 2010. Automatic classification of daily fluid intake. https://doi.org/10.4108/ICST.PERVASIVEHEALTH2010.8906

[22] Paul D. Loprinzi, Ellen Smit, and Sara Mahoney. 2014. Physical Activity and Dietary Behavior in US Adults and Their Combined Influence on Health. *Mayo*

Clinic Proceedings 89, 2 (2014), 190–198. https://doi.org/10.1016/j.mayocp.2013.09.018

[23] Paul Poirier, Thomas D. Giles, George A Bray, Yuling Hong, Judith S. Stern, F. Xavier Pi-Sunyer, and Robert H. Eckel. 2006. Obesity and Cardiovascular Disease: Pathophysiology, Evaluation, and Effect of Weight Loss. *Arteriosclerosis, Thrombosis, and Vascular Biology* 26 (2006), 968–976.

[24] Parisa Pouladzadeh, Shervin Shirmohammadi, and Rana Al-Maghrabi. 2014. Measuring Calorie and Nutrition From Food Image. *IEEE Transactions on Instrumentation and Measurement* 63, 8 (2014), 1947–1956. https://doi.org/10.1109/TIM.2014.2303533

[25] Laavanya Rachakonda, Saraju P. Mohanty, and Elias Kougianos. 2020. iLog: An Intelligent Device for Automatic Food Intake Monitoring and Stress Detection in the IoMT. *IEEE Transactions on Consumer Electronics* 66, 2 (2020), 115–124. https://doi.org/10.1109/TCE.2020.2976006

[26] Giovanni Schiboni and Oliver Amft. 2018. Automatic Dietary Monitoring Using Wearable Accessories. In *Seamless Healthcare Monitoring: Advancements in Wearable, Attachable, and Invisible Devices*, Toshiyo Tamura and Wenxi Chen (Eds.). Springer, 369–412. https://doi.org/10.1007/978-3-319-69362-0_13

[27] Dale A Schoeller. 1995. Limitations in the assessment of dietary energy intake by self-report. *Metabolism: Clinical and Experimental* 44 (1995), 18–22. https://doi.org/10.1016/0026-0495(95)90204-X

[28] Nur Asmiza Selamat and Sawal Hamid Md. Ali. 2020. Automatic Food Intake Monitoring Based on Chewing Activity: A Survey. *IEEE Access* 8 (2020), 48846–48869. https://doi.org/10.1109/ACCESS.2020.2978260

[29] J.C. Witschi. 1990. Short-Term Dietary Recall and Recording Methods. In *Nutritional Epidemiology*. Vol. 4. Oxford University Press, 52–68.

[30] World Health Organization. 2021. Obesity and overweight. https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight

[31] World Health Organization. 2022. *World health statistics 2022: monitoring health for the SDGs, sustainable development goals*. World Health Organization, Geneva. https://apps.who.int/iris/handle/10665/356584 Section: ix, 125 p..

[32] Kazuya Yamaguchi, Taketo Yamaguchi, Takeo Odaka, and Hiromitsu Saisho. 2006. Evaluation of gastrointestinal motility by computerized analysis of abdominal auscultation findings. *Journal of Gastroenterology and hepatology* 21, 3 (2006), 510–514.

[33] Yifan Yang, Wenyan Jia, Tamara Bucher, Hong Zhang, and Mingui Sun. 2019. Image-based food portion size estimation using a smartphone without a fiducial marker. *Public Health Nutrition* 22, 7 (2019), 1180–1192. https://doi.org/10.1017/S136898001800054X

[34] Bethany Yon, Rachel Johnson, Jean Harvey-Berino, and Beth Gold. 2006. The Use of a Personal Digital Assistant for Dietary Self-Monitoring Does Not Improve the Validity of Self-Reports of Energy Intake. *Journal of the American Dietetic Association* 106 (09 2006), 1256–9. https://doi.org/10.1016/j.jada.2006.05.004

[35] Zuoyi Zhang, Huizhe Zheng, Sawyer Rempel, Kenny Hong, Teng Han, Yumiko Sakamoto, and Pourang Irani. 2020. A Smart Utensil for Detecting Food Pick-up Gesture and Amount While Eating. In *Proceedings of the 11th Augmented Human International Conference* (Winnipeg, Manitoba, Canada) *(AH '20)*. Association for Computing Machinery, New York, NY, USA, Article 2, 8 pages. https://doi.org/10.1145/3396339.3396361

[36] Bo Zhou, Jingyuan Cheng, Mathias Sundholm, Attila Reiss, Wuhuang Huang, Oliver Amft, and Paul Lukowicz. 2015. Smart table surface: A novel approach to pervasive dining monitoring. In *2015 IEEE International Conference on Pervasive Computing and Communications (PerCom)*. 155–162. https://doi.org/10.1109/PERCOM.2015.7146522

[37] Fengqing Zhu, Marc Bosch, Insoo Woo, SungYe Kim, Carol J. Boushey, David S. Ebert, and Edward J. Delp. 2010. The Use of Mobile Devices in Aiding Dietary Assessment and Evaluation. *IEEE Journal of Selected Topics in Signal Processing* 4, 4 (2010), 756–766. https://doi.org/10.1109/JSTSP.2010.2051471