Exploring Challenges in Automated Just-In-Time Adaptive Food Choice Interventions

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ABSTRACT

A healthy diet lowers the risk of developing diseases like diabetes, obesity and different types of cancers and cardiovascular conditions. Persuasive systems have already shown promise in changing user's nutrition through the strategy of monitoring and retrospectively visualizing (bad) eating behavior. In contrast emerged the idea of systems proactively offering help before such behavior even occurs, i.e. before a food choice has been made. Recent advances within the sensor-enrichment of smartphones and wearable technologies have made it possible to develop new behavior change intervention techniques, such as Just-In-Time Adaptive Interventions (JITAI). Within this work, we discuss challenges towards technology-supported, completely automated JITAIs to support healthy food choices. We derive the challenges based on existing literature, and discuss future research opportunities that would benefit users towards achieving a healthier eating behavior.

CCS CONCEPTS

•**Human-centered computing** →**Human computer interaction (HCI);** *Ubiquitous and mobile computing;*

KEYWORDS

Just-In-Time Intervention; Adaptation; Context; Sensing System; Personalization

1 INTRODUCTION

Of 52,8 million deaths worldwide in 2010, 65% are linked to diseases like diabetes, obesity, and different types of cancers and cardiovascular conditions. A healthy lifestyle, including a healthy diet, can lower the risk of developing such conditions [12].

Persuasive technologies have been utilized in the health care space to help people develop new habits, with nutrition being no exception. Within this domain, persuasive systems have mostly relied on the strategy of reflection on (unhealthy) food choices, accompanied with fixed logging reminders [1], user-activated support [11] or feedback on past behavior [2]. On the contrary emerged the idea of a persuasive system that *proactively* offers help before such behavior even occurs, i.e. before a food choice has been made.

Within this paper, we explore the fit of technology-supported **Just-In-Time Adaptive Interventions (JITAIs)** to support healthy food choice. We deduce open challenges regarding **completely automated** JITAIs, i.e. JITAIs that *sensorially monitor* user's state, behavior and her contextual surroundings, *automatically predict* appropriate intervention time-frames from the sensed data and finally, *automatically fire* an appropriate intervention method within that time-frame. Hence, such JITAIs require no input neither by the user nor by the designer once deployed and running. We derive the challenges from related literature and discuss future research opportunities.

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2 BACKGROUND

Ubiquitous sensor-equipped smartphones and consumer wearable devices have been recognized as valuable tools in the quest for a healthy lifestyle and nutrition by the research community as well. Within the domain of healthy nutrition, a well justified behavior change strategy is self-monitoring of food intake. Although effective, the required degree of user's commitment of keeping a food diary can quickly become burdensome, leading to a notable drop of user involvement and even disengagement [4, 6]. Hence, the focus nowadays has been shifted to developing smart sensor systems that automatically record user's eating behavior [13, 27].

Whether manually or automatically tracking food in a diary, the behavior change intervention in such systems takes place *after* the eating event. Yet, adults consume 92% of the plate content once served [26]. Following this work, Rahman et al. [17] surveyed users about the appropriate timing of a smartphone intervention assisting in healthy eating decisions. 43% of users claimed the right moment to be *before* the actual meal takes place. In other words, users expressed needing help in deciding what they *should eat* in the future, and not just in determining what they *have been eating* in the past.

To understand how and when such a suggestion-intervention should take place, we must understand the process of food choice in the first place. The sciences of nutrition and psychology responsibly claim that factors influencing food intake and food choices are not limited to user-related factors. Additionally, the context of the eating event, including the event's social surroundings, physical factors, time-related characteristics and potential distractions, plays an undeniable role in the food selection process [24]. It is therefore of highest importance to consider user's environment when designing food choice mobile interventions.

The increasing sensor-enrichment of smartphones and advances in the field of consumer wearable technologies, as well as the relevant data analysis methods based on machine learning, made it possible to track and understand a person's health, behavior and surrounding factors. The scope of data that gets collected covers various aspects, being physical activity tracking, sleep, body weight or fat percentage, as well as medical conditions, for instance blood sugar or blood

pressure. This enables the use of new intervention techniques to influence our behavior, one of which are JITAIs. A JITAI is an intervention that adapts its support to the user and her surroundings "over time to an individual's changing status and contexts", aiming at delivering support "at the moment and in the context that the person needs it most and is most likely to be receptive" [23]. In other words, *when* and *how* to trigger a JITAI present a JITAI's central components [15]. The intuition behind the JITAIs compliance to healthy food choice interventions lies within the fact that a JITAI might detect physical, cognitive and social windows of opportunity within the food choice process and nudge the user towards a healthier food choice.

Though an effective method in supporting behavior change [22], JITAIs are still a rather novel intervention method. Some current research on JITAIs includes sensor-based detection of user's availability episodes to engage in an intervention [18], predicting stress-episodes from sensed data [19] as well as offering distractions in case of emotional eating strikes [3]. However, there still exist many open questions regarding JITAIs for healthy food choices with emphasis on their central *when* and *how* components.

3 CHALLENGES IN AUTOMATED JUST-IN-TIME FOOD CHOICE INTERVENTIONS

In favor of bringing the concept of JITAIs closer for discussion, we introduce Sam:

Sam is around mid-twenties and works from 9 to 6, 5 days a week. In order to be at work on time, Sam usually skips breakfast or eats something quickly, such as a bagel. Sam's lunch includes going to a restaurant in the vicinity of work, around noon, with colleagues. If lunch was not filling, Sam snacks between three and four. For dinner, Sam prefers cooking quick meals at home when not meeting friends, which happens to be around two to three times a week. Sam prefers fish over meat, loves ice cream and would like to consume more vegetables and less refined sugar.

A sensing system could expose several food choice moments by observing Sam's daily routine and surroundings. The simplest case would be identifying lunch by observing the time (around noon), the signal of other devices from Sam's social circle (work colleagues) and GPS-location (location of work). An appropriate JITAI could, half an hour before noon [25], suggest a couple of meal items with a high content of vegetables that are offered by restaurants around Sam's work. The values for context variables in cases of breakfast, snack and dinner could be detected in a similar way.

Consider now the subsequent plot:

Today is a very sunny day in Samland and Sam wants something for snack. Sam decided to take an ice cream from the best ice cream shop in the world, that just happens to be around the corner. Sam gets up from the desk and asks colleagues to join. They head to the shop and indulge in the ice cream, feeling very happy about it. Sam feels no regret although aware vegetable sticks would have been the healthier option.

On these terms, the sensing system could predict Sam's excursion to the ice cream shop by monitoring many sensors: (1) the accelerometer (Sam standing up), (2) the microphone (Sam inviting colleagues), (3) GPS-location tracking (Sam on the route to the ice cream shop), (4) browser history (Sam googling the ice cream shop 5 minutes before), (5) temperature (it is a hot, sunny day in Samland) and (6) contextual history (Sam visiting the ice cream shop in 90% of similar occasions). Although we have a lot of information on Sam, we still don't know which sensors, or their combinations, are reliable indicators of Sam's behavior and whether we have covered all the influencing context. However, assuming the system could really guess Sam's food choice, the next step would be a JITAI. To design such interventions, we need to explore more about Sam and especially how Sam can be persuaded to make a healthier food choice instead. Since we know that Sam already decided to go for ice cream and that ice cream is Sam's favorite food, suggesting to get fresh fruit instead might be hopeless. But would it help Sam more, if the intervention suggests a maximum number of ice cream scoops or a flavor with less sugar? Or would it be better to suggest an after work running trail to burn off the calories and state a better snack recommendation for tomorrow? Maybe no intervention should be triggered at all, as it might arouse negative feelings around a happy event and evoke a bad mood?

The told scenarios have led us to the following four central questions around JITAIs for healthy food choices:

(1) What are the (context) factors that influence a person's food choices?
(2) What kind of sensing system would a person accept to use in order to monitor the context factors from (1)?
(3) When should the intervention system offer support and when not?
(4) In what way should the intervention offer support?

Within the following subsections, we discuss current literature's stand regarding these questions.

3.1 Contextual Factors to be Sensed

Sam's colleague Max eats breakfast daily, mostly starting it with a bowl of fruits followed by cereals and milk. Together with Sam and other colleagues, Max goes to lunch. In the evening, Max and Max's partner join for dinner at home. Max almost never snacks. Max would like to cut the body fat percentage.

The comparison demonstrates the differences in goals each person has from an intervention and differences in food choice patterns based on existing habits and the current environment. Environmental stimuli such as the number of people present, food accessibility, eating locations, ambient temperatures and lighting, time of consumption, etc., all can trigger a change in food intake and food choice [24]. It is therefore important to capture as many types of users and as many contextual stimuli affecting user's nutrition as possible [5], as this will clearly give the deepest and most comprehensive overview of user's life.

However, different contextual variables differently contribute to the eating event along different individuals [17]. That is, for a person who skips breakfast, has lunch in the vicinity of work and dinners with friends at a restaurant downtown, the same contextual model as for a person who eats most of her meals at home, will simply not work. Such diversity complicates the conceptualization of a one-size-fits-all approach on what contextual factors to track.

3.2 Acceptance of Automated Context Sensing

Modern ubiquitous and wearable technologies (i.e. fitbits), have already proven themselves successful at, e.g., physical activity estimation. Nevertheless, users would still often forget to wear the tracking device [1, 21] or to charge it overnight [8, 9]. Other users argue that the design of the tracking device does not fit their style [21].

On the contrary, using off-the-shelf sensor-enabled smartphones to monitor user behavior along several health dimensions benefits in at least two ways. First, users need solely one device which they tend to keep close or in which vicinity they move around [14]. Second, latest smartphones can track up to 13 contextual variables[1], all integrated within one device. Yet, the second benefit also presents a limitation, as no further upgrade is possible if insisting on the integration property. On the contrary, using the combination of a smartphone, a Microsoft band, a wearable microphone and an Affectiva Q sensor, Rahman et al. [17] predicted about-to-eat moments covering eleven different data streams. However, participants have expressed comfort difficulties with a wearable microphone, as well as privacy concerns with special regards to social acceptability. Additionally, a multi-device sensing system proportionally increases the burden of remembering to wear the device, as well as the budget load. Driven by the requirements of a comfortable form and an integrated solution, Carroll et al. [3] implemented a sensing system placed in a bra that automatically detects emotions.

3.3 Finding the Appropriate Time to Fire the Intervention

By definition, a JITAI offers support only in contexts when the user is in need of it and when the user can engage in the intervention. This means that the collected data must be analyzed with the goal of establishing user's most needed and most receptive moments.

The first work informing on the timing of sensor-triggered JITAIs found availability episodes in which the person can engage in the intervention [18]. The analysis of the collected sensor data and self-reports found that in particular location, affect, activity type, stress, time and day of the week play significant roles in predicting availability. Subsequent work explored visualization possibilities of time-series sensor data, and evaluated these with experts to inform the design of stress-related JITAIs. The experts considered the contextual visualizations helpful for the purpose of designing time, modality and content aspects of the JITAI [20]. In another study, [19] developed a system that automatically detects major stress episodes from timely-discontinued, sensory-acquired, stress-related data streams.

Some studies claim that a food decision made 30 minutes before the actual eating event, can already suffice to make a healthier food choice compared to when the same decision is made at the starting time of an eating event [25]. Rahman et al.[17] have followed this premise by predicting 30 minutes in advance about-to-eat moments. An emotion sensing, bra-integrated wearable [3] detects emotions as arousal and valence, that are held responsible for emotional eating. Such prediction windows could be marked as appropriate intervention windows of opportunity.

[1] https://developer.android.com/guide/topics/sensors/sensors_overview.html

3.4 Finding a Proper Intervention Method

Sam running late for the next meeting at work and looking for a quick lunch break in between will not be able to spend an hour cooking a healthy meal. On the contrary, a backpacker going low on budget by the end of the journey will most probably appreciate a recipe suggestion more than a lunch menu at a restaurant. Therefore, the intervention method must adapt to the user's situation and goal.

Users whose goal is to eat less will appreciate simple breathing or visualization distraction methods in overcoming food cravings [3, 11]. A user opting for a more healthy diet will desire healthy alternatives over unhealthy food choices [11]. This aligns with findings that users wish for personalized interventions [3].

When asked what type of intervention should accompany them before making a food decision, most users stated wanting a simple calorie calculator prompt for the food they are about to eat, followed by a visualization of the food that has been eaten in the past. Next were reminders for a balanced meal of food groups or macro-nutrients, as well as calorie allowance [17]. Persuasive, personalized food suggestions did not find their way on the list. Yet these might take a big portion of cognitive load of the user.

However, in a qualitative study of Dennison et al. [7], young adults expressed scepticism over the accuracy and feasibility of context-triggered advice, suggesting that advice on not to do something "would produce counterproductive effects by drawing attention towards unhealthy but attractive behavior choice" and unintentionally "worsen your mood ... or draw attention towards feelings or situations that would otherwise be unnoticed." Thus, the accuracy in personal fit of such suggestions must be ensured to do no harm.

4 RESEARCH OPPORTUNITIES

As denoted in the above presented research, smartphone- and wearable-based JITAIs present a growing opportunity towards eating self-management. With the main challenge of completely automating JITAIs for food choice, future research should address such problems as generalization of eating patterns, on-the-fly personalization and acceptance of JITAIs, in order to optimally support users with divergent desires and capabilities.

Exploration of the connection between user types and influencing contextual variables. The process of food choice, even though depending on the environment of the eating event, is a decision every individual makes for herself by including and excluding various (contextual) factors within the process. However, based on the similarity of users' patterns of daily order, we might detect repeating situations where help with food choice is particularly needed. Future research should therefore include exploratory studies with as many and as different target groups as possible, with the goal of finding and assigning contextual variables to such situations. In that way, the sensing system could on-the-fly turn on and off relevant sensors, leading to a reduction of the number of necessary data streams to be tracked. This in particular benefits privacy-aware users and leads to simplification of data analysis methods.

Development of sensing systems that fit user's everyday life. Future work should investigate ways that make the sensing system more fitting into a user's life by not compromising the context sensing scope of interventions. A heterogeneous system consisting of several wearable device modules might work if the user could craft

and personalize it [10]. Yet, the emerging trend of the Internet of Things (IoT) could move this work into the direction of a network of connected, ubiquitous devices and environmental sensors communicating with each other, as already proven to be feasible in the field of dementia research [16]. An application of an IoT approach, for example in the home of the user, would bring the benefit of providing ubiquitous sensor data about the user's daily routines and habits while being nearly invisible for the user. Such pervasive data collection transfers the burden of acquiring data from users onto the network. But, future research regarding privacy and data security in such systems is essential work.

Exploration of (in)appropriate JITAI time-frames and intervention methods. Prospective research has to investigate how often to intervene and in what way to intervene in order to avoid JITAIs becoming a burden and/or annoyance to the user. For example, we should ask ourselves whether all about-to-eat moments [17] are appropriate time-frames for a JITAIs, and what makes those moments appropriate or not. There exists a lack of research in determining situations when JITAIs might be particularly effective, and when they produce an opposite effect.

Short- and long-term personalization of JITAIs. Subsequent work needs to explore the possibility of personalizing JITAIs in terms of the user herself, eg. her emotions (eg. pizza as comfort food), moods (eg. user does not feel like cooking tonight) or personalities, in order to evoke only positive feelings and evade the negative ones.

5 CONCLUSION

We presented current literature on JITAIs and their efforts to tackle the four identified challenges towards completely automated JITAIs for healthier food choices. Although JITAIs can be seen as a promising approach to influence peoples eating behavior, a user-centered design approach is necessary to explore the feasibility of JITAIs in user's daily life. Therefore, the discussion of future research opportunities focuses on the user's acceptance and engagement with JITAIs. We conclude that interdisciplinary research of computer scientists, psychologists, sociologists, nutritionists and engineers is needed.

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REFERENCES

[1] Frank Bentley and Konrad Tollmar. 2013. The power of mobile notifications to increase wellbeing logging behavior. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 1095–1098.

[2] Frank Bentley, Konrad Tollmar, Peter Stephenson, Laura Levy, Brian Jones, Scott Robertson, Ed Price, Richard Catrambone, and Jeff Wilson. 2013. Health Mashups: Presenting statistical patterns between wellbeing data and context in natural language to promote behavior change. *ACM Transactions on Computer-Human Interaction (TOCHI)* 20, 5 (2013), 30.

[3] Erin A Carroll, Mary Czerwinski, Asta Roseway, Ashish Kapoor, Paul Johns, Kael Rowan, and MC Schraefel. 2013. Food and mood: Just-in-time support for emotional eating. In *Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on*. IEEE, 252–257.

[4] Eun Kyoung Choe, Nicole B Lee, Bongshin Lee, Wanda Pratt, and Julie A Kientz. 2014. Understanding quantified-selfers' practices in collecting and exploring personal data. In *Proceedings of the 32nd annual ACM conference on Human factors in computing systems*. ACM, 1143–1152.

[5] Sunny Consolvo, Katherine Everitt, Ian Smith, and James A Landay. 2006. Design requirements for technologies that encourage physical activity. In *Proceedings of the SIGCHI conference on Human Factors in computing systems*. ACM, 457–466.

[6] Felicia Cordeiro, Daniel A Epstein, Edison Thomaz, Elizabeth Bales, Arvind K Jagannathan, Gregory D Abowd, and James Fogarty. 2015. Barriers and negative nudges: Exploring challenges in food journaling. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. ACM, 1159–1162.

[7] Laura Dennison, Leanne Morrison, Gemma Conway, and Lucy Yardley. 2013. Opportunities and challenges for smartphone applications in supporting health behavior change: qualitative study. *Journal of medical Internet research* 15, 4 (2013).

[8] Thomas Fritz, Elaine M Huang, Gail C Murphy, and Thomas Zimmermann. 2014. Persuasive technology in the real world: a study of long-term use of activity sensing devices for fitness. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 487–496.

[9] Rebecca Gulotta, Jodi Forlizzi, Rayoung Yang, and Mark Wah Newman. 2016. Fostering Engagement with Personal Informatics Systems. In *Proceedings of the 2016 ACM Conference on Designing Interactive Systems*. ACM, 286–300.

[10] Katrin Hänsel, Natalie Wilde, Hamed Haddadi, and Akram Alomainy. 2015. Challenges with current wearable technology in monitoring health data and providing positive behavioural support. In *Proceedings of the 5th EAI International Conference on Wireless Mobile Communication and Healthcare*. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 158–161.

[11] Anne Hsu, Jing Yang, Yigit Han Yilmaz, Md Sanaul Haque, Cengiz Can, and Ann E Blandford. 2014. Persuasive technology for overcoming food cravings and improving snack choices. In *Proceedings of the 32nd annual ACM conference on Human factors in computing systems*. ACM, 3403–3412.

[12] World Cancer Research Fund International. 2014. The link between food, nutrition, diet and non-communicable diseases. (2014). http://www.wcrf.org/sites/default/files/PPA_NCD_Alliance_Nutrition.pdf

[13] Azusa Kadomura, Cheng-Yuan Li, Koji Tsukada, Hao-Hua Chu, and Itiro Siio. 2014. Persuasive technology to improve eating behavior using a sensor-embedded fork. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 319–329.

[14] Nicholas D Lane, Mu Lin, Mashfiqui Mohammod, Xiaochao Yang, Hong Lu, Giuseppe Cardone, Shahid Ali, Afsaneh Doryab, Ethan Berke, Andrew T Campbell, et al. 2014. Bewell: Sensing sleep, physical activities and social interactions to promote wellbeing. *Mobile Networks and Applications* 19, 3 (2014), 345–359.

[15] Inbal Nahum-Shani, Shawna N Smith, Bonnie J Spring, Linda M Collins, Katie Witkiewitz, Ambuj Tewari, and Susan A Murphy. 2016. Just-in-Time Adaptive Interventions (JITAIs) in mobile health: key components and design principles for ongoing health behavior support. *Annals of Behavioral Medicine* (2016), 1–17.

[16] Zhibo Pang, Lirong Zheng, Junzhe Tian, Sharon Kao-Walter, Elena Dubrova, and Qiang Chen. 2015. Design of a terminal solution for integration of in-home health care devices and services towards the Internet-of-Things. *Enterprise Information Systems* 9, 1 (2015), 86–116.

[17] Tauhidur Rahman, Mary Czerwinski, Ran Gilad-Bachrach, and Paul Johns. 2016. Predicting About-to-Eat Moments for Just-in-Time Eating Intervention. In *Proceedings of the 6th International Conference on Digital Health Conference*. ACM, 141–150.

[18] Hillol Sarker, Moushumi Sharmin, Amin Ahsan Ali, Md Mahbubur Rahman, Rummana Bari, Syed Monowar Hossain, and Santosh Kumar. 2014. Assessing the availability of users to engage in just-in-time intervention in the natural environment. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 909–920.

[19] Hillol Sarker, Matthew Tyburski, Md Mahbubur Rahman, Karen Hovsepian, Moushumi Sharmin, David H Epstein, Kenzie L Preston, C Debra Furr-Holden, Adam Milam, Inbal Nahum-Shani, et al. 2016. Finding significant stress episodes in a discontinuous time series of rapidly varying mobile sensor data. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, 4489–4501.

[20] Moushumi Sharmin, Andrew Raij, David Epstien, Inbal Nahum-Shani, J Gayle Beck, Sudip Vhaduri, Kenzie Preston, and Santosh Kumar. 2015. Visualization of time-series sensor data to inform the design of just-in-time adaptive stress interventions. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 505–516.

[21] Patrick C Shih, Kyungsik Han, Erika Shehan Poole, Mary Beth Rosson, and John M Carroll. 2015. Use and adoption challenges of wearable activity trackers. *IConference 2015 Proceedings* (2015).

[22] Joshua M Smyth and Kristin E Heron. 2016. Is providing mobile interventions" just-in-time" helpful? an experimental proof of concept study of just-in-time intervention for stress management.. In *Wireless Health*. 89–95.

[23] Donna Spruijt-Metz, Cheng KF Wen, Gillian O'Reilly, Ming Li, Sangwon Lee, BA Emken, Urbashi Mitra, Murali Annavaram, Gisele Ragusa, and Shrikanth Narayanan. 2015. Innovations in the use of interactive technology to support weight management. *Current obesity reports* 4, 4 (2015), 510–519.

[24] Nanette Stroebele and John M De Castro. 2004. Effect of ambience on food intake and food choice. *Nutrition* 20, 9 (2004), 821–838.

[25] Eric M VanEpps, Julie S Downs, and George Loewenstein. 2016. Advance Ordering for Healthier Eating? Field Experiments on the Relationship Between the Meal Order–Consumption Time Delay and Meal Content. *Journal of Marketing Research* 53, 3 (2016), 369–380.

[26] Brian Wansink and Katherine Abowd Johnson. 2015. The clean plate club: about 92% of self-served food is eaten. *International Journal of Obesity* 39, 2 (2015), 371–374.

[27] Shibo Zhang, Rawan Alharbi, William Stogin, Mohamad Pourhomayun, Bonnie Spring, and Nabil Alshurafa. 2016. Food watch: detecting and characterizing eating episodes through feeding gestures. In *Proceedings of the 11th EAI International Conference on Body Area Networks*. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 91–96.