Understanding People's Perceptions of Approaches to Semi-Automated Dietary Monitoring

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The respective benefits and drawbacks of manual food journaling and automated dietary monitoring (ADM) suggest the value of semi-automated journaling systems combining the approaches. However, the current understanding of how people anticipate strategies for implementing semi-automated food journaling systems is limited. We therefore conduct a speculative survey study with 600 responses, examining how people anticipate approaches to automatic capture and prompting for details. Participants feel the location and detection capability of ADM sensors influences anticipated physical, social, and privacy burdens. People more positively anticipate prompts which contain information relevant to their journaling goals, help them recall what they ate, and are quick to respond to. Our work suggests a tradeoff between ADM systems' detection performance and anticipated acceptability, with sensors on facial areas having higher performance but lower acceptability than sensors in other areas and more usable prompting methods like those containing specific foods being more challenging to produce than manual reminders. We suggest opportunities to improve higher-acceptability, lower-accuracy ADM sensors, select approaches based on individual and practitioner journaling needs, and better describe capabilities to potential users.

CCS Concepts: • **Human-centered computing → Empirical studies in ubiquitous and mobile computing**.

Additional Key Words and Phrases: Automated Dietary Monitoring, ADM, Personal Informatics, Self-Tracking, Food Journaling, Semi-Automated Tracking

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1 INTRODUCTION

Food journaling or dietary monitoring is widely used to monitor diet, which is crucial for building healthy eating habits, managing weight, and improving chronic health conditions [26, 45, 53]. While many clinical uses of manual food journaling typically involve short engagement (e.g., 24-hour diet recalls), achieving these larger health-related goals usually requires long-term engagement with food journaling. However, people often anticipate manual food journaling as burdensome and tedious, leading to users abandoning tracking of commercial journaling apps in several months or even weeks or days [12, 43, 58, 59]. The reliability of manual entry has also been questioned, as people can (un)intentionally misrecord their food consumption such as portion size [19, 26]. To address manual entry's burdens and reliability [26], a long thread of Ubicomp research has explored automated dietary monitoring (ADM) as an alternative, more objective approach [7]. Current ADM systems put sensors on body locations—including mouth, ear, forehead, jaw, neck, wrist, and chest—to automatically detect the moment in which people intake food and/or what they ate [7, 70]. Researchers have made progress on

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enhancing recognition capabilities and lowering burdens through inventing new sensors, combining multiple sensors, and improving recognition algorithms [7, 41, 63, 81]. However, ADM systems are still in the exploratory phase, and most applications are not practical enough to be used in everyday life. For example, ADM systems may be uncomfortable or bulky [2, 3, 63, 71], may cause social discomfort [32, 64, 85], or may not be accurate enough for some monitoring goals [7].

Given the respective benefits and drawbacks of fully-automated and fully manual tracking, Choe et al. [19] proposed that semi-automated tracking approaches can strike a balance of these two methods. In food journaling, a semi-automated system is formed by approaches to automatic capture certain food information (e.g., when a person eats, what a person eats, and/or the eating context) and approaches to prompting for more details (e.g., confirming or adding more information) to support collecting accurate records while lowering overall burden. In addition, semi-automated systems can help address some of ADM's limitations, such as a lack of engagement with and reflection on the collected data [19], which are crucial for successful behavior change. Prior work suggests that some manual burdens can better help habit formation of dietary self-monitoring than fully automated approaches [81].

Although semi-automated food journaling seems promising for balancing burden with utility, we have limited understanding of which of the wide array of ADM sensors and approaches for manually adding context people would find useful and usable in their everyday lives. Current ADM studies mainly focus on evaluating and improving detection and recognition capabilities, and less is understood about how people anticipate the acceptability and burdens of different kinds of wearable ADM sensors. The varied detection capabilities of ADM sensors also influence what information clarifying prompts can include. For example, approaches such as wrist motion may simply be able to detect when a person ate [78], while ADM sensors that leverage audio or jaw motion may be able to detect food texture [6, 18, 22, 44, 79] and wearable camera approaches can include images [5, 77, 79]. However, we have a limited understanding of what information people would feel helpful for adding details. Understanding people's perceptions of and preferences toward wearable ADM sensors and manual journaling prompts can suggest promising directions for designing semi-automated systems that balance manual journaling effort and ADM's acceptability and utility.

We therefore conducted two speculative survey studies with 600 responses in total to understand how people anticipate the acceptability and burdens of different approaches to automatic capture and prompting for details, two fundamental parts that form semi-automated food journaling systems. Understanding anticipations is valuable since ADM sensors are currently under exploration by researchers but largely not commercially available, and anticipated benefits frequently drive interest in and adoption of new technology [54, 82]. We surveyed people on their perspectives of ten types of wearable ADM sensors from current ADM literature, including wrist-worn sensors with image, sound, or motion modalities, eyeglass sensors with cameras, and necklace sensors to detect swallowing sounds [5–7, 15, 18, 22, 41, 44, 63, 70, 77–79, 86]. Informed by the detection capabilities of different ADM sensors [5, 7, 22, 41, 67, 70, 77–79], we surveyed people on six prompting mechanisms containing food information that ask people to add or confirm what they ate, including specific food information (e.g., broccoli), food groups (e.g., vegetable, grain), food textures (e.g., crunchy and soft foods), pictures or short video clips of food intake moments, food audio clips, and reminders to manually log food. From participant's responses to validated scales for technology acceptability [82] and user burden [76] and open-ended explanations, we answer the research questions:

- RQ1) How do the form factors and sensing approaches used in different on-body ADM sensors influence how people anticipate their burden and acceptability?
- RQ2) What kinds of prompts do people anticipate being most willing to respond to get information about foods?

- RQ3) When do people anticipate being most willing to respond to a prompt to add more detail about what they ate?

We found that anticipated physical, social, and privacy burdens mainly influenced participants' willingness to wear on-body ADM sensors. Sensors' body locations and detection modalities also affected how people felt about these burdens, with sensors on the face or which collected more human-interpretable signals typically having greater burdens. Continuously wearing ADM sensors may introduce greater physical and privacy burdens, while wearing sensors strictly while eating may introduce greater social and interaction burdens. These findings surface a tradeoff between ADM systems' detection capability and acceptability, with non-facial sensors having higher anticipated acceptability and usability than facial sensors but generally having lower detection capability. Participants were generally more willing to receive prompts soon after they ate or at a time they decided, and prompts containing information that aligned with their food journaling goals, helped them recollect what they ate, or would reduce the time burden of responding to prompts. We point to opportunities for improving highly-acceptable, but lower-accuracy ADM systems like wrist-worn sensors, and point to a need to align semi-automated approaches with individual's goals and clinical practitioner's needs.

We contribute:

- An empirical understanding of how people anticipate perceiving different on-body ADM sensors. We found participants had more negative anticipated perceptions of sensors around facial areas due to their physical and social burdens, although these systems generally have higher detection capabilities. For example, participants worried facial ADM sensors might constrain muscle movements associated with eating, influence social eating experiences, and trigger unfriendly questions around food journaling. Participants expressed greater privacy concerns for sensors that leveraged image or sound modalities or were explicitly placed in front of their bodies. We also surfaced a tension between continuously wearing ADM sensors and wearing them only while eating, with continuous wearing causing physical and privacy burdens, and eating-only wearing introducing social and interaction burdens.
- An understanding of how people anticipate approaches to prompting for clarification in food journaling, finding a similar tradeoff that the prompts with higher anticipated acceptability are more difficult to produce. Participants anticipated prompts containing detailed food information such as specific foods or food pictures more acceptable, as they would better support their journaling goals, help them recall what they ate, or be faster to respond to. Participants were more willing to receive prompts either shortly after eating or at a time they set themselves, suggesting limits of time-intensive offline processing of sensed data.
- Discussion of design and development directions for making semi-automated food journaling more acceptable and useful, informed by participant's anticipations. We point out the value of increasing the accuracy of more acceptable, but less accurate sensors, and suggest mixing manual activation with automating sensing to mitigate privacy burdens. We also offer advice on selecting from semi-automated approaches based on journaling goals and practitioner needs, processing sensed information to improve prompting approaches, and better conveying systems' capabilities to potential adopters.

2 RELATED WORK

Semi-automated approaches to dietary monitoring draw on prior systems for manual food journaling, automated dietary monitoring, and prompting and notifications. Although significant research has contributed novel approaches to both manual and automatic food journaling, we have less understanding of how people anticipate approaches to combining the two to support semi-automated food journaling.

2.1 Manual and Semi-Automated Food Journaling Systems

Manual food journaling has a long history in using paper records and digital systems to monitor and assess people's diets. In nutritional epidemiology, paper records such as food frequency questionnaires (FFQ), dietary recalls, and food record logging are the primary methods to assess one's dietary behaviors [83]. These mechanisms usually require people to write down what they ate and/or more general dietary habits either by themselves or with an interviewer's assistance, typically in a 24-hour recall or shortly after eating [83]. However, most people tend to wait until the end of the day to log, rather than logging soon after they eat [43]. Besides paper approaches, scholars have developed digital systems to increase compliance and reduce errors, such as PmEB [80], Barcode Ed [74], MAHI [56], DECAF [25], and MyBehavior [65]. However, these systems still heavily rely on manually entering foods, though they incorporate some automated methods to help lower the tracking burden such as searching databases, scanning barcodes, and leveraging voice recording or photo taking [34, 74, 75, 80]. Beyond the burden of manual entry, people have to remember to track their food regularly or set up daily reminders in order to have detailed logs [26, 38]. The widespread adoption of commercial food journaling apps, such as MyFitnessPal, MyPlate, and Weight Watchers, has also led to an increased understanding of how people experience the activity in everyday life. For example, food journaling is a topic many people find sensitive, leading some to hesitate or avoid journaling in front of others [26].

Researchers have proposed that semi-automated approaches can address manual tracking's drawbacks by combining manual entry with automated detection [19, 49]. On the one hand, automated tracking could lower capture burdens by automatically detecting that a person is eating, collecting information about what and how much they ate, and/or prompting the manual journaling process. On the other hand, manual tracking allows people to journal data that may be difficult to automatically capture, and the act of entering data can enhance people's awareness of their health behaviors. Therefore, semi-automated tracking approaches have been regarded as a potentially promising way to support tracking and journaling beyond short recall periods. Studies have applied the semi-automated approach to other tracking and journaling domains including sleep, stress, personalized health feedback, and self-care plans [1, 14, 20, 49, 65].

Although digital manual journaling systems have been often studied and put into practice, how the approach could be integrated with automated approaches has been less explored. In food journaling, the two primary sub-tasks of a semi-automated approach are detecting when a person is eating and triggering follow-up manual efforts. A practical instantiation of this approach starts with an on-body sensor that automatically infers when a person is eating. Once a person is eating and eating activity has been detected, several courses of action could be pursued to prompt the individual for more information. Past research systems have generally advanced one sub-task or the other [20, 48, 49]. Understanding how people anticipate different approaches to integrating these sub-tasks can help identify promising strategies for implementing semi-automated food journaling.

2.2 Automated Dietary Monitoring

Automated dietary monitoring (ADM) systems aim to automatically detect when a person is eating, and/or capture information about what or how much a person has eaten [7]. ADM systems have leveraged sensors like accelerometers, gyroscopes, and microphones to support detection in many on-body sensing locations, including facial stick-on sensors [22], earbud sensors [6], eyeglass sensors [5, 86], intraoral sensors [70], neckband sensors [18, 44], chest-worn cameras [77, 79], and wristband sensors [78]. Body locations and sensor types decide what food information can be detected. For example, wrist-worn ADM systems have used accelerometers to identify when a person is eating by detecting hand-to-mouth gestures [78]. Wearable cameras capturing food pictures have leveraged image recognition to identify the specific food a person has eaten [77, 79]. Intraoral sensors have measured temperature and jawbone movement to detect when a person is eating and recognize the texture of their food (e.g., chewy, soft, water content) [70]. Current ADM systems also often combine multiple sensors to improve detection capability and accuracy [7, 37], but performance has varied based on the underlying activity being detected and sensing capabilities. For example, the accuracy rate of eyeglasses with inertial sensors has performed reasonably well in naturalistic settings, such as reading F1-scores above 90%, while approaches leveraging neck-worn, chest, and wrist sensors were usually around 75% to 85% [7]. The heavy computation of some approaches relies on offline (e.g., asynchronous) processing, such as training Random Forest classifiers to identify food types [70].

Beyond accuracy, prior studies have noted that ADM sensors may not be well-received in everyday life, expressing concerns around social acceptability, physical comfort, and privacy. Social acceptability is a critical factor influencing wearable technology's uptake and usage [32, 64, 85]. People may be less willing to use innovative wearable technology with new form factors and gesture interactions in social settings [32, 85], since many people fear drawing attention or looking awkward in public [64]. Towards physical comfort, studies suggest hands and arms are the most socially acceptable locations, and wearable technology should avoid private or sensitive body locations [39, 64, 85]. In order to detect eating activities, ADM sensors often leverage locations which may be less comfortable or restrict movement. For example, neck sensors have to be tightly attached to the skin, and ear-worn sensors may be embedded in a pad within the ear to detect sounds, which are less practical for sustained use [3, 15]. People also express concerns about the privacy of others within the wearer's proximity when wearing ADM sensors [69, 85]. These concerns are most notable around image-capture approaches to ADM, since cameras would inevitably record video or photos of bystanders [29, 30, 71]. Some researchers have proposed approaches to mitigating privacy, such as filtering photos or restricting what is captured [29, 30, 79]. However, current understanding of wearable technology's wearability, social acceptability, and privacy issues are mostly domain-agnostic, offering a general sense of what body locations are preferred or what circumstances influence anticipated interest. We have less understanding of how the social and emotional nature of food journaling impacts anticipated preferences among techniques, which can help us better develop viable semi-automated journaling approaches.

2.3 Prompting and Notifications

Prompts in manual food journaling systems aim to increase people's adherence to self-tracking through frequent and regular notifications [8, 66]. Within Ubicomp, a long history of research has aimed to understand what influences people's willingness to respond to notifications and develop systems which account for those constraints. Researchers found various factors influencing people's willingness to respond to notifications, such as their timing, what other task(s) a person is doing, and the notification's content [57]. For example, in one study, people were most willing to receive notifications from diet apps within an hour after eating or in the evening [38]. Choi et al. [21] found people tend to ignore notifications when they are busy or in social settings, while they are also more likely to respond during light social engagements such as casual talks [21].

Prior studies supporting manual food journaling have proposed different approaches to timing prompts. Ecological Momentary Assessment (EMA) approaches often send notifications at points throughout the day to enable collecting in-the-moment data, but may disturb people's daily schedule and cause abandonment [42, 66]. Some systems allow people to set up schedules so that notifications can fit into their daily routines [8]. Taking the 24-hour dietary recall as an example, although allowing people to report their diet retrospectively makes the technique less burdensome, this recollection has led its accuracy to be questioned [51]. Researchers have therefore proposed combining contextual information with notifications to enhance adherence to self-tracking and help manual entry [10, 16, 65, 66]. For example, Rabbi et al. [66] leveraged passively collected contextual information to assist people in recalling memories when answering questions in the evening.

Semi-automated food journaling systems can take different approaches to prompting follow-up manual efforts based on ADM sensors' distinct detection capabilities, from asking to enter what was eaten based on detecting that a person ate to asking for verification of what specific foods or what amounts were detected to be eaten. We therefore examine when people want to be prompted, and how different food journaling prompts would influence people's willingness to respond.

3 METHODS

To understand people's anticipated preferences around different wearable ADM sensors and prompting mechanisms, we opted to run a speculative survey. Anticipations can influence people's adoption of and willingness to use new technologies [82]. Speculative surveys are often used in Human-Computer Interaction (HCI) as a precursor to implementing and deploying complex systems to offer insights into which of different system options should be pursued, and provide suggestions on how researchers and practitioners can improve the technology [39, 54]. Various survey scales have been invented to evaluate people's attitudes toward proposed technologies, such as the User Burden Scale (UBS) [76], acceptability of accuracy [46], and Technology Acceptance Model (TAM) [82]. Understanding from these speculative surveys can help inform what approaches to ADM that researchers and practitioners should invest development effort into improving and evaluating.

We built and deployed two complementary surveys which focused on how people anticipate the relative burdens and acceptability of wearable ADM sensors and manual journaling prompt methods. We developed and iterated the survey through several rounds of pilot tests among the authors and feedback from convenience samples (e.g., friends, students). We initially drafted a single survey, with participants giving feedback both on wearable ADM sensors and manual journaling prompts. This draft took about 40 minutes to complete, and pilot participants frequently commented that they stopped thinking as deeply about the questions past a point. To improve response quality, we therefore separated questions about ADM sensors (RQ1) and food journaling prompts (RQ2 & RQ3) into two separate surveys. The ADM survey took approximately 20 minutes to complete, while the prompting survey took approximately 15 minutes. Both surveys were classified as exempt by our institution's IRB because they contain no more than minimal risk and do not collect any identifiable information. The supplemental materials contain the full list of questions for both surveys.

3.1 Wearable ADM Sensor Survey Structure

Apart from consent, the wearable ADM sensors survey contained three sections: (1) introducing semi-automated journaling and specific approaches, (2) gathering perspectives on these approaches, and (3) collecting demographics. (1) We first introduced the idea of semi-automated food journaling and asked participants' about their past food journaling experiences. For participants who had experience or interest in food journaling, we asked them to identify which of common food journaling goal(s) described by prior literature applied to them (e.g., healthy eating, weight, chronic condition management, curiosity, no specific goal [23, 26, 34, 35, 45, 56, 80]). We then described ten different wearable ADM sensors (Table 1) based on six popular on-body locations from previous studies: face, ear, eye, mouth, neck, chest, and wrist [2, 3, 5–7, 15, 18, 22, 30, 41, 44, 63, 70, 71, 77–79, 86]. The detection mechanisms varied by body location, such as EMG or piezoelectric sensors to detect facial movements, accelerometers to detect hand-to-mouth gesture, microphone to detect sounds, and cameras to take pictures [7]. We used a blend of both low- and high-fidelity sketches (Figure 1) and descriptions drawn from the prior work to introduce how these wearable ADM sensors might function and what sensing streams they leverage. It is important to note that the fidelity of sketches has the potential to influence respondent's perspectives on the design approaches [13], and higher-fidelity sketches of ADM sensors may further have some influence on perspectives (e.g., if size or weight of the device were more apparent). (2) The survey then included six sets of questions for each of the ten wearable ADM sensors. We included three subscales adapted from the Technology Acceptance Model [82] to understand people's intentions to use, anticipated usefulness (whether reducing manual journaling burden and adding engagement), and anticipated ease of use toward wearable ADM sensors. For

Table 1. Introductions of on-body ADM sensors included in the Wearable ADM Sensor survey.

Name	Written Description	Exemplar(s)
EarJawMotion	A small stick-on disposable sensor, roughly 1cm in diameter (like a smallband-aid), placed in front of the ear close to the cheek. It detected when people ate from jawbone's movement.	[7, 22]
EarSound	A sensor embedded in a typical wireless earbud (like AirPods), placed in the earcanal. It detected when people ate from the chewing sound.	[6, 7]
WristGestureMotion	A sensor embedded in a typical smartwatch (like an Apple Watch). It detected when people ate by recognizing the gesture of bringing food to their mouths.	[7, 78]
WristGesture&Image	A sensor embedded in a typical smartwatch (like an Apple Watch). It detected when people ate by recognizing the gesture of bringing food to their mouths and its embedded camera.	[7, 73]
WristSound	A sensor embedded in a typical smartwatch (like an Apple Watch). It detected when people ate by recognizing ambient sounds.	[7, 78]
EyeMuscleActivity	A pair of smart glasses, a little heavier than typical glasses. It detected when people ate from their facial muscle contractions.	[7, 36]
EyeImage	A pair of smart glasses with an embedded camera, a little heavier than typicalglasses. It detected when people ate via taking pictures and processing them.	[5, 7]
NeckSound	A tight necklace sensor, like a choker. It detected when people ate from their swallowing sounds.	[7, 18, 67]
IntraoralTempMotion	A mold a few millimeters thick which went over people's teeth, like if they were getting braces. It detected when they ate by measuring temperature inside the mouth and its movement.	[7, 70]
ChestImage	A wearable camera, about the size of a badge or a brooch. It detected when people ate via taking pictures and processing them	[7, 77, 79]

example, for the intention-to-use subscale, we asked: *"I would be willing to use the following tracker(s) in my daily life."* We also included three subscales from the User Burden Scale to understand participants' anticipated physical, time and social, and privacy burdens for each ADM sensor [76]. For example, for the physical burden subscale, we asked *"There would be no physical discomfort with using the following tracker(s)."* and *"I would be reluctant to wear the following tracker(s) because it may create physical discomfort."* Subscales varied between one and three closed-form questions. For each subscale, we included one follow-up open-ended question to better understand why participants had such anticipations (*e.g., Please explain: for the kinds of trackers you thought would have more or less physical discomfort, why do you think so?*). We fixed the order of ten sensors for each question, grouping sensors with the same body locations together so that participants could readily compare and contrast approaches to ADM sensing. (3) The survey ended up with optional demographic questions.

3.2 Prompting Survey Structure

The food journaling prompts survey similarly included three sections, with the aim to instead understand responders' anticipated burdens and acceptability toward different prompting mechanisms. The survey asked participants' anticipations toward different prompting mechanisms (RQ2), and their willingness of when to receive prompts (RQ3). (1) It first described how different prompting mechanisms worked and the corresponding manual journaling effort each required. Drawn from previous ADM studies and manual food journaling studies [5, 22, 41, 67, 70, 77, 78, 78–80], we included six prompting mechanisms for manually logging or editing different food-related information on a mobile app (Table 2). These six prompting mechanisms were: food textures, food groups, specific foods, food pictures/videos, food audio clips, and manual reminders. The follow-up actions varied by notifications' content, such as adding more details, confirming the information, or fully manually logging food in a diet app (Figure 1). We did not further specify how logging and editing might occur in the diet app

Table 2. Introductions of strategies for prompting included in the Prompting survey.

Name	Written Description	Exemplar(s)
Food textures	Prompts containing information about the texture of the food (e.g., crunchy and soft foods) that people just ate, asking them to add more details.	[70]
Food groups	Prompts containing information about the food group (e.g., vegetable, grain, etc.) that people just ate, asking them to add more details.	[70]
Specific foods	Prompts containing information about the specific food (e.g., broccoli) that people just ate, asking them to confirm or edit it.	[41]
Food picture/video	Prompts containing pictures or short video clips for food intake moments, helping people to recall meals and manually log food in diet app.	[5, 77, 79]
Food audio clips	Prompts containing short audio clips for food intake moments, helping people to recall the eating context, such as the sound of being in a restaurant.	[78]
Manual reminder	Prompts reminding people to manually log food in a diet app as the tracker couldn't recognize what they ate.	[22, 67, 78]

Table 3. Participants' self-reported demographic information.

Gender	Age	Ethnicity	Education	Ann. House Income	Prior Experience	Goal
Female: 304 (50.84%) Male: 289 (48.33%) Non-binary /3rd gender: 5 (0.84%)	18-27: 116(19.76%) 28-37: 108 (18.40%) 38-47: 97 (16.52%) 48-57: 101 (17.21%) 58-64: 104 (17.72%) 65+: 61 (10.39%)	White: 390 (66.78%) Black: 82 (14.04%) Asian: 48 (8.22%) Latino: 32 (5.48%) Multiracial: 32 (5.48%)	<high school: 2 (0.34%) High school: 46 (7.71%) In college: 167 (27.97%) Bachelor deg.: 184 (30.82%) In grad school: 37 (6.20%) Grad deg.: 161 (26.97%)	<=35K : 147(24.83%) 35K−50K: 86 (14.53%) 50K−75K: 110 (18.58%) >=75K : 249(42.06%)	Wearable tech: Yes: 361 (60.27%); No: 238 (39.73%) Food journaling: Yes: 396 (66.00%); No: 204 (34.00%)	Multiple: 255 (42.50%) Healthy eating: 129 (21.50%) Manage condition: 17 (2.83%) Weight: 164 (27.33%) Curiosity: 7 (1.17%) No specific goals: 28 (4.67%)

(e.g., via free text description, via a search in a food database) to focus feedback on how each approach might aid in recollection rather than input burden. (2) We asked the same subscales from the Technology Acceptance Model [82] and User Burden Scale [76] as in the wearable ADM survey, except adding the mental burden scale and removing the physical and privacy burden scales as less applicable to a prompting system. We also asked open-ended questions for each subscale (*e.g., Please explain: for the kinds of information you thought would have more or less of the time and social burden, why do you think so?*). In addition, we asked when people would be willing to receive prompts: *"In general, I would be willing to receive a notification to journal my food."* We asked participants to rate their willingness for five different timings (*e.g., while I am eating, a short time after I finish eating, one hour after I finish eating, two or three hours after I finish eating, and at the time set myself*), which were often seen in manual food journaling studies [38, 83]. (3) Participants could also optionally report their demographics.

3.3 Participant Recruitment

We built the two surveys on Qualtrics and deployed them on Prolific in August 2021. Because demographic factors like socioeconomics and age influence people's access to both food and technology [24, 84], and anticipations of technologies [62], we prioritized recruiting a representative sample over stratifying by participants' food journaling experiences or goals. We used the platform's representative sample feature, which aims to recruit participants which approximate the gender, educational, ethnic, and socioeconomic backgrounds of the United States [17]. We required participants to be at least 18 years old and be fluent in English. For both surveys, we paid people a living wage ($15/hour) for responding to our study ($5 for the 20-minute ADM sensors survey and $3.75 for the 15-minute prompts survey). We collected 600 complete responses in total (299 for the ADM sensor survey and 301 for the prompts survey), excluding four responses from people who took less than three minutes to answer the surveys. One hundred and six participants took both surveys.

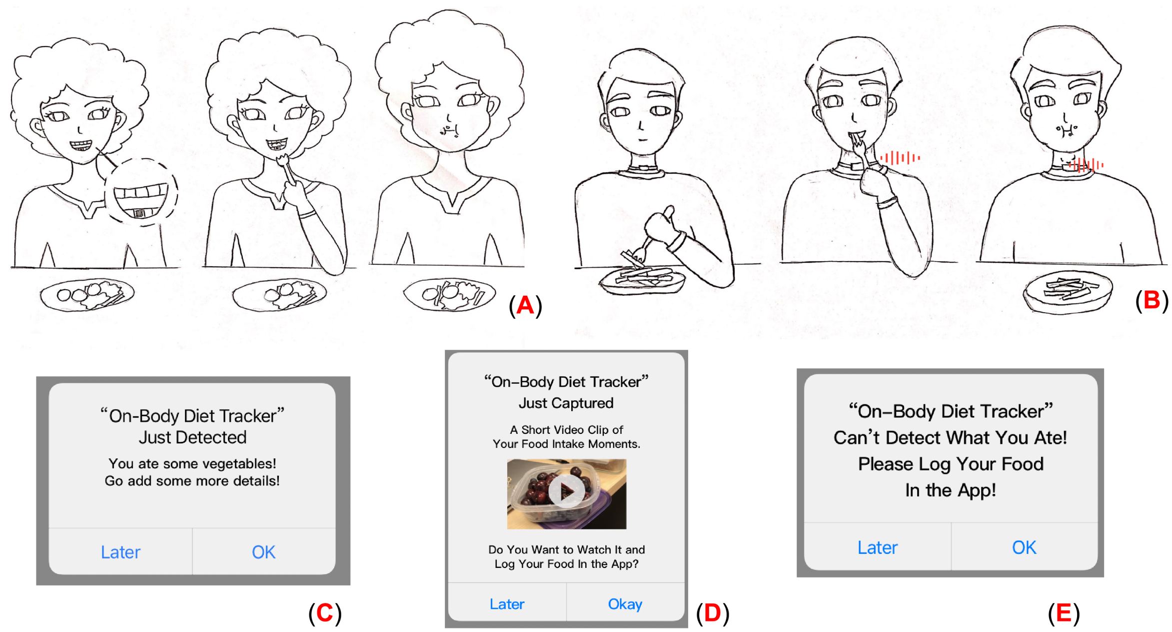

Fig. 1. Example screenshots of low- and hi-fidelity sketches for wearable ADM sensors and prompting mechanisms included in the two surveys. (A) IntraoralTempMotion, an intraoral temperature sensor; (B) NeckSound, a neck-worn sound sensor; (C) Prompts containing food groups; (D) Prompts containing food pictures or videos; (E) Reminders to manually log food.

Table 3 describes how participants self-identified their demographics. Participant ages ranged from 18 to 90 (mean=43.86, sd=16.32). Our participants were highly educated overall, with 595 (99.66%) having a high school education or higher, and 382 (63.99%) having at least a bachelor's degree. The median annual household income of our participants fell between \$50,000 and \$75,000. Two-thirds of participants (n=361) had experience journaling their food through food journaling apps (n=302), paper diaries (n=105), social media (n=32), and taking pictures (n=31). Notably, more than half of our participants had experiences with wrist-worn wearable technology. Popular devices were Apple Watch (n=163), Fitbit (n=200), Garmin (n=17), and the Samsung Smartwatch (n=19). Most of our participants had weight management goals (n=164), healthy eating goals (n=129), or multiple goals (n=255).

3.4 Analysis

We used mixed-effect ordered logit models to quantitatively analyze participants' anticipated preferences and perspectives toward the different wearable ADM sensors and food journaling prompts. As many of the TAM and UBS subscales contained multiple questions, we calculated average rates for their subscales. We treated Likert ratings of subscales' close-ended questions as ordinal responses. For ADM sensors, We treated sensors' types (ten levels) and subscales (seven levels) as categorical fixed effects, and participant IDs as a random effect. For different types of prompts, we similarly treated prompts' types (six levels) and subscales (seven levels) as categorical fixed effects, and participant IDs as a random effect. For people's preference of when to receive prompts, we treated the willingness level Likert rating as an ordinal response, different timings (five levels) as categorical fixed effects, and participants IDs as a random effect. We also grouped ADM sensors based on body locations (e.g., facial and non-facial) and detection modalities to explore their influences on people's anticipations. We added participants' food journaling goals as a categorical fixed effect in our models. We collapsed the food journaling goal categories into three types: health (healthy eating and chronic condition management), weight management, and casual (curiosity and no specific goal), as sample size for many sub-goals was small and initial analysis indicated minimal differences. All participants who indicated multiple goals included at least one health goal, so we categorized their goals as health-related. We used false discovery rate corrections to correct multiple comparisons in post-hoc tests.

We qualitatively coded the open-ended responses by thematic analysis [11]. Two authors first read and open coded 30 responses individually to generate a codebook. Through meeting and discussing the codes to reach the consensus, the authors generated a formal codebook with definitions and examples for each code. The final codebook contained three parent codes (*RQ1: ADM sensors; RQ2: content of prompts; RQ3: when to receive prompts*) and eight subcodes in total (*RQ1: physical burden, privacy burden, social burden, and interaction burden; RQ2: goal-related, ability in helping recall, and time and social burdens of responding to prompts; RQ3: attitudes toward each timing*). The first author coded all the survey responses by using the formal codebook. We refer to individual participants from the ADM sensor survey with SXX and participants from the prompt survey with PXX.

4 RESULTS

We organize our results based on our three research questions, first describing factors influencing burdens and acceptability of ADM sensors (RQ1) and then describing content and timing of manual journaling prompts (RQ2 & RQ3). Participants were mainly concerned about physical, social, and privacy burdens of ADM sensors, with the detection modalities of different sensors and their body locations influencing how participants anticipated these burdens in alignment with their food journaling goals. Participants preferred to receive information in prompts which aligned with their food journaling goals, could help with recalling what they ate, and would take less time to respond to. Participants were more willing to receive prompts when their memories were still fresh, at leisure, or less frequently.

4.1 RQ1: How ADM Sensors' Form Factors Influence People's Anticipated Burden and Acceptability

Overall, participants were more willing to wear non-facial sensors (e.g., chest and wrist) than facial sensors (eye, ear, intraoral, and neck; *z=25.748, p<0.0001, 95%CI 0.879-1.05 higher on a 5-point Likert scale*) (Figure 2). Participants additionally found the wrist form factor more acceptable than the chest (*z=11.861, p<0.0001, 95%CI 0.640-0.938 higher on a 5-point Likert scale*). Among facial sensors, they were more willing to wear sensors placed on the upper face (e.g., eye and ear) than ones around the lower facial area (e.g., intraoral and neck) (*z=6.474, p<0.0001, 95%CI 0.216-0.445 higher on a 5-point Likert scale*). Participants were more willing to wear sensors with motion, multi-, or image modalities than the sound modality (*z=-10.114, p<0.0001, 95%CI 0.1989-0.420 lower on a 5-point Likert scale*), with no significant difference in people's overall attitudes among the three approaches (*p>0.05*). Participants' food journaling goals also influenced their willingness to wear on-body ADM sensors. Among participants with health-related, weight, or casual goals (e.g., curiosity or no specific goals), participants interested in monitoring food for health were most willing to wear ADM sensors (*z=4.609, p<.0001, 95%CI 0.257-0.812 higher on a 5-point Likert scale*), while people with casual goals were least willing to try ADM sensors (*z=-3.770, p=0.0002, 95%CI 0.265-1.186 lower on a 5-point Likert scale*). For example, S267 had no interest in food journaling, and questioned ADM sensors' necessity: *"I am old school when it comes to some things, my eating habit is not something I want tracked"*. In contrast, S232 had a weight loss goal, and wished ADM sensors could strictly monitor his daily calorie intake: *"I've struggled with my weight all my life. I've tried diets, Weight Watchers, FitBit, and even my Apple Watch. How bout a device that measures caloric intake and sends shocks or buzzes when thresholds are exceeded?"* Some participants felt people with specific health conditions would more greatly appreciate ADM sensors: *"If I were a person who was in need of extreme regulation to my diet for medical reasons, similar to those who wear devices for*

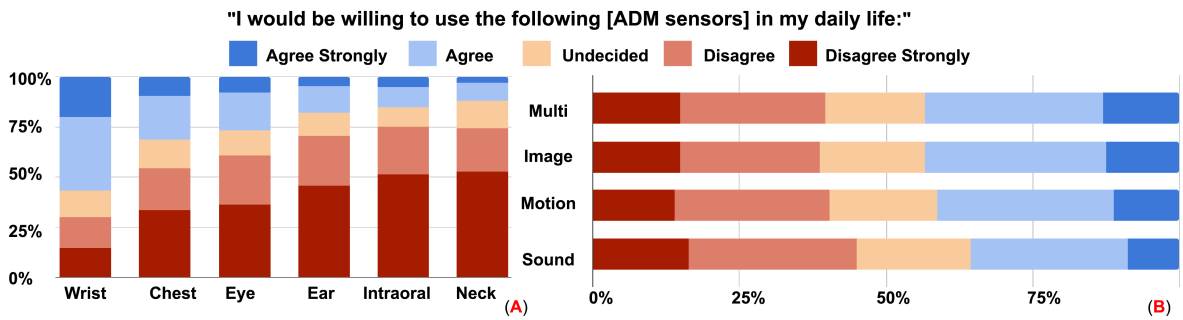

Fig. 2. (A) Participants were more willing to put ADM sensors on non-facial areas (e.g., wrists and chests) than facial areas, while being most unwilling about sensors put on the lower face (e.g., necks or inside mouths). (B) Participants were more willing to wear sensors with the motion capability, multi-, sound modalities than the image one.

heart issues or diabetes, I would be much more likely to accept those that are more closely regulatory, and or possible to prompt eating entries more often" (S177).

Participants' preferences were influenced by the anticipated physical, social, and privacy burdens of wearing different on-body ADM sensors. They associated body locations, especially facial areas, with these burdens. Modality, such as image and sound sensors, also influenced how participants anticipated privacy burdens. We also surfaced tensions between continuously wearing on-body ADM sensors and wearing sensors while eating. Though continuously wearing may better support detection of when and how much a person eats, it elicited greater physical and privacy concerns. Wearing sensors while only eating, on the other hand, had greater anticipated social and engagement burdens.

4.1.1 Physical Burden. Participants' anticipated physical discomfort of wearing on-body ADM sensors differed by body locations (Figure 3 A). Participants felt ADM sensors placed on facial areas (eyes, ears, neck, and intraoral) would have higher physical burden (*z=-31.781, p<0.0001, 95%CI 1.0360-1.1932 lower on a 5-point Likert scale*) than non-facial (chest and wrist) sensors. Specifically, among all the body locations, participants anticipated intraoral sensors to have the greatest physical burden (*z=-13.989, p<0.0001, 95%CI 1.05256-1.5418 lower on a 5-point Likert scale*). They further anticipated lower physical burden for the upper facial (e.g., eye and ear) sensors than the lower facial ones (e.g., intraoral and neck) (*z=10.116, p<0.0001, 95%CI 0.35945-0.56408 higher on a 5-point Likert scale*). Besides people's general discomfort with putting something on the skin [39, 85], participants often worried that on-body ADM sensors would impede how their muscles or organs would move and function while they ate, particularly in their face.

On-body locations matter for food journaling sensors' comfort since eating is a complex physiological process that engages more than 30 nerves and muscles [71]. Participants worried wearing ADM sensors around the face area would constrain their face and/or neck muscle movements when they ate, negatively influencing their food intake and digestion experience. For example, participants worried that neck sensors would *"make swallowing uncomfortable and make me uncomfortably aware of the act of eating"* (S194). S100 even imagined that neck sensors *"may actually choke the person."* S280 suspected intraoral sensors would disrupt people chewing food: *"Intraoral would be difficult because anything in your mouth besides food feels weird and would reduce the enjoyment of eating."* Some participants felt they would constantly worry that facial sensors might fall off: *"when I'm moving/chewing and might consistently fall out of my ear which would be frustrating"* (S6).

4.1.2 Social Burden. Participants also felt body location would impact the social burden of ADM sensors, anticipating greater social burden for sensors around the facial area (*Z= -17.878, P<0.0001, 95%CI 0.5081-0.6537*

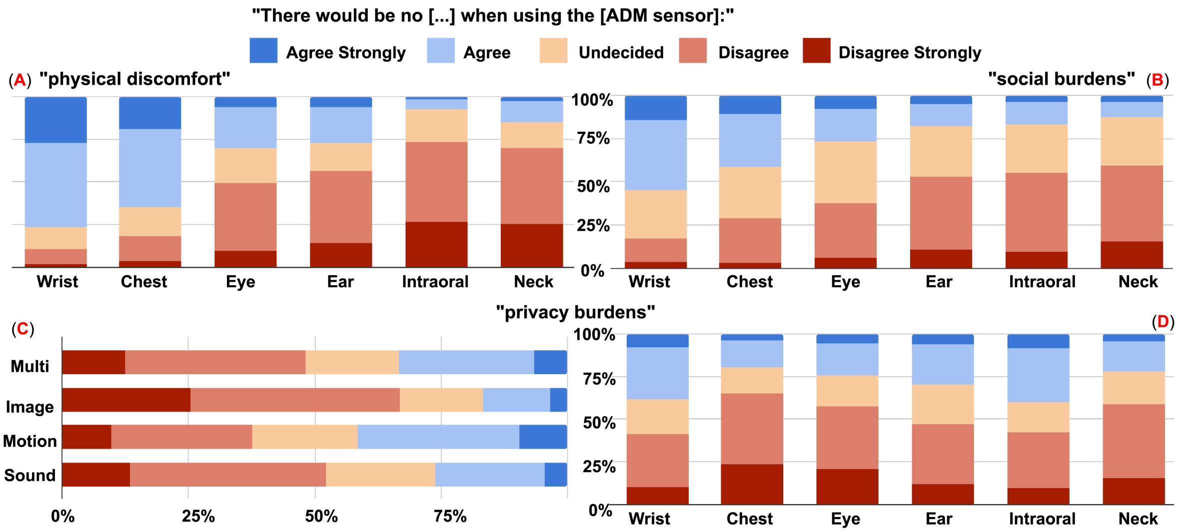

Fig. 3. (A) Participants generally agreed that sensors placed on wrists and chests would have lower physical discomfort, while anticipating greater physical discomfort around sensors put on the face (eyes, ears, necks, and intraoral). (B) Participants felt sensors placed on wrists and chests would have no or less social burden than ones around the facial area (eye, ear, intraoral, and neck). (C) Participants overwhelmingly agreed that motion sensors would fewer privacy burdens than multi-, sound, and image modalities. (D) Participants anticipated fewer privacy burdens from intraoral and wrist sensors than sensors put on ears, eyes, necks, and chests.

lower on a 5-point Likert scale) than non-facial area. Among facial sensors, social burdens were anticipated to be greater for intraoral and neck sensors than eye and ear sensors (*Z=4.760, P<0.0001, 95%CI 0.10894 - 0.30279 higher on a 5-point Likert scale*) (Figure 3 B). Aligned with prior work [9, 53], participants worried that noticeable on-body ADM sensors would cause social stigma, especially for people struggling with body image issues. They were also concerned that on-body ADM sensors would disrupt their social eating experiences. Facial sensors were anticipated to be most noticeable, and may impact people's ability to socialize with others while eating. Participants also felt sensors more similar to daily accessories and technologies, such as wrist sensors and facial sensors, would have lower social burden.

Although people usually track food to improve health or manage weight [26], studies have suggested that these motivations are often stigmatized socially, and people are therefore reluctant to disclose their monitoring behaviors [9, 53]. Qualitative results suggested that participants with weight management goals tended to be more concerned about social burdens than ones with health-related goals. Food journaling is often associated with body image issues [53], and participants with weight management goals worried about socially-visible ADM sensors since it could be *"really frustrating to have people ask you about what you're using, or what you're doing especially when it's related to losing weight"* (S27). In comparison, some participants anticipated no or few social burdens if they leveraged ADM sensors to improve health: *"I don[']t believe there will be a social burden because nowadays people are not judgmental and very open[-]minded for those taking care of their health"* (S299).

Eating is often a social activity, and participants were also concerned about whether wearing on-body ADM sensors would be a distraction when eating with others. First, having sensors on some body locations, especially ones around the face area, might impede people's physiological ability to interact with others during social eating events: *"They would make it harder to see/hear or otherwise be a big distraction"* (S135). For example, S91 felt earbud sensors *"might change hearing ability"* and intraoral sensors *"might change speaking ability."* Second, participants worried the effort to ensure whether sensors could work successfully during eating might lead to wearers paying too much attention to the device itself rather than the people who they eat with. For example, S16 described, *"The trackers that include glasses would have a social burden because I would have to focus on keeping the glasses on and keeping them focused on the food so that it would detect the food."*

As suggested by prior work [32, 64], participants preferred on-body ADM sensors similar to wearable devices or other daily worn objects common in everyday life, as they were anticipated to have higher social acceptance and be less noticeable in public. Participants generally felt wrist sensors had the least social burden, likely due to familiarity with commercial wrist sensors : *"People tend to wear smart watches or fitbits daily so it's not as strange as the other options"* (S24). Though participants felt facial sensors were more noticeable, they felt ones similar to accessories, such as eyeglasses, earphones, and necklaces would be more acceptable: *"ear sounds would have less of a social burden because nowadays everyone wears a wireless headphone when they go out places and it is very common to see"* (S8).

4.1.3 Privacy Burden. Participants anticipated greater privacy burdens for sensors placed on the front of people's bodies (e.g., eye, neck, and chest) than ones either in more discreet locations (e.g., ear and wrist) or inside the mouth (*z=-9.534, p<0.0001, 95%CI 0.2408-0.3888 lower on a 5-point Likert scale*). Among facial sensors, they felt greater privacy burdens for eye (*z=-4.509, p<0.0001, 95%CI 0.1418-0.4940 lower on a 5-point Likert scale*) and neck sensors (*z=-3.145, p=0.0022, 95%CI 0.0564-0.4912 lower on a 5-point Likert scale*) than ear and intraoral ones. Among input modalities, participants also felt the image modality would have the greatest privacy burden (*z=-10.368, p<0.0001, 95%CI 0.971633-1.3236 lower on a 5-point Likert scale*), and the motion modality would have the least privacy burden (*z=9.686, p<0.0001 95%CI 0.3828 -0.6489 higher on a 5-point Likert scale*). Participants worried that the detection mechanisms of ADM sensors may be able to capture information irrelevant to food, since some sensors might need to be continuously on. Participants had greater privacy concerns for image and sound sensors than motion sensors, as they felt people's movements were not as sensitive. In addition, participants anticipated sensors placed in front of their bodies to be more of a privacy concern because they were more widely visible.

Participants' perspectives confirmed prior work around privacy issues in ADM sensors [79], worrying whether ADM sensors' detection mechanism would allow for capturing sensitive activities irrelevant to eating. Since ADM sensors often detect and track food-related data automatically, participants worried sensors would continuously capture images or sounds (Figure 3 C). For example, S50 felt that image and sound modalities could *"record conversations and other private things as well as cameras which can record live footage at any time."* Since eating is often a social experience accompanied by other activities, participants worried continuously detecting and capturing would include other things than food information: *"Trackers that track movement, sounds or images that might include other activities or behaviors besides eating would be invasive (e.g., singing, kissing, laughing, etc.)"* (S279). In comparison, participants often felt motion sensors detecting eating movements *"aren't really a concern at all"* (S58) since they *"don't seem to be able to tell anything else about a person"* (S74).

Our data further suggested certain body locations (Figure 3 D) also influence whether people anticipated privacy burdens for ADM sensors. Participants felt sensors placed in front of the body, such as chest and eye sensors, would have greater privacy concerns since these locations have a broad field of view and may be more likely to detect activities unrelated to eating. For example, S172 felt eyeglass sensors could see whatever human eyes do than wrist-worn sensors: *"I think the eye cameras would have more of a privacy burden than the wrist camera because it is literally seeing what you see from your eye height."*

However, some participants felt the privacy risks of ADM sensors were not a major drawback. First, participants felt the tradeoff of reducing the burden of manual journaling burdens was worth the privacy violations: *"I'm not really worried about the privacy as much as the inconvenience"* (S18). Second, a few participants felt information about people's eating was insensitive: *"While it is possible for the devices to pick up sounds for the environment, it* *does not necessarily mean that your privacy is at risk. It is a tracking device and it service[s] to track food consumption. So I would not be as concerned about privacy"*(S182).

4.1.4 Tensions between Wearing Continuously versus Wearing while Eating. Our qualitative data surfaced tensions between wearing ADM sensors continuously versus wearing them only while eating. ADM sensors theoretically require people to wear them continuously to automatically capture when a person is eating and information about what they eat. However, some participants felt they would instead prefer to put on ADM sensors only while eating, anticipating high physical and privacy burdens around continuous wear. However, participants felt this approach would create more social and interaction burdens around remembering to turn on the device and drawing attention to it.

Current working mechanisms of on-body ADM sensors require people to wear sensors all the time so they can detect when a person is eating and automatically collect food-related information [7, 30, 41]. However, participants expressed that continuous wear could bring physical and privacy burdens: *"I just think anything you have to decide to put on and wear every day is going to be more difficult to use, especially the glasses that are heavier than normal glasses, the item you wear IN your mouth, and the item you wear on your cheek. Those are not natural things to wear during the day and would be more difficult"* (S12). S29 felt it was difficult to ensure some on-body sensors would be sticky enough to stay on the skin all the day: *"I'm unsure how the items would be attached to me-sticky ness that is hard to come off, would it slip off at the end of the day."* Continuously and passively capturing information, such as people's hand gestures or ambient environment sounds [2, 7, 78], similarly introduced privacy concerns. For example, S171 worried: *"A camera following you everywhere?? what happens if that video gets leaked your whole life from peeing to pooping is out there."* Some participants therefore suggested only using sensors when people decided to collect their food information: *"anything that automatically takes pictures or records sounds would be a privacy burden. [I] would prefer something that would take a picture only of plate when personally triggered"* (S139).

However, participants anticipated that wearing ADM sensors just during eating would raise social and interaction burdens. Participants wished ADM sensors to be less noticeable, but wearing or manually initiating ADM sensors whenever people ate would attract other's attention when eating in social settings: *"It would be very awkward in social situations to either install or set up one of these devices and I would feel self conscious about wearing one"* (S219). Some sensors which may be difficult to place or set up, such as intraoral ones, could create more social burdens: *"Once again if it requires a mold in your teeth, that will probably be a social burden of inserting mold and taking out, can you even talk with it in?"* (S1). The action of wearing sensors while eating would also be a distraction since *"if you have to remember to put them on, it might take away from the spontaneity of eating/drinking"* (S10). Prior food journaling studies suggest that people tended to abandon food journaling because of interaction burdens such as forgetting or the fatigue of frequent journaling [26]. Participants anticipated that putting on ADM sensors every time they ate would introduce similar burdens: *"Having to take a tracker on and off, such as a necklace or chest tracker would reduce the amount I'd like to use it"* (S38). Participants also feared they would: *"have to worry about remembering to take them on or off every time you go to eat something"* (S48). Therefore, some participants wished ADM sensors could be worn all the time. For example, S40 said, *"Ensuring the item could be in use consistently without having to remember to put it on when eating would be more likely to increase my engagement with food journaling."*

4.2 RQ2: What Food Journaling Prompts People are Most Willing to Respond to

Participants tended to prefer prompts that contained information related to their food journaling goals, could help them recollect food information, or would be faster to respond to. Among food journaling prompts (Figure 4 A), participants were more willing to receive prompts containing specific foods (*$z=10.739$, $p<0.0001$, 95%CI 0.797-1.317 higher on a 5-point Likert scale*), food groups (*$z=9.711$, $p<0.0001$, 95%CI 0.696-1.216 higher on a 5-point Likert scale*),

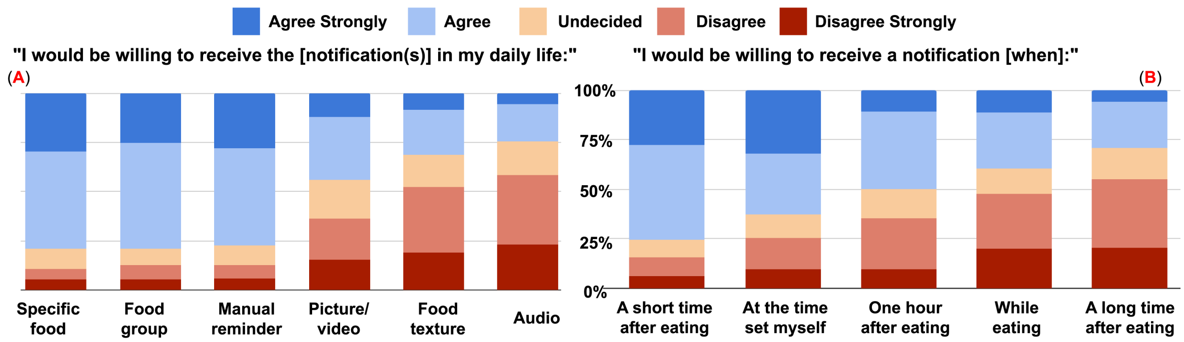

Fig. 4. (A) Participants were overwhelmingly more willing to receiving prompts containing specific food information, reminders to manually log food, and food groups. Participants were neutral or marginally positive about receiving prompts containing either food pictures or videos. Participants felt negative about receiving food texture and food audio clips. (B) Participants were most willing to receive prompts either a short time after eating or at time set themselves. Participants were positive about receiving prompts one hour after eating, and were less willing to receive prompts while they are eating or a long time after eating.

or just a reminder to manually log food (*z=9.216, p<0.0001, 95%CI 0.643-1.158 higher on a 5-point Likert scale*) than pictures or videos, food texture, or audio.

4.2.1 People's Journaling Goals Resulted in Different Needs for Manual Journaling Prompts. Participants preferred prompts that contained information relevant to their food journaling goals. Among six types of prompts, participants with health or weight goals were more willing to receive notifications containing food groups (*z=3.154, p=0.003, 95%CI 0.166-1.210 higher on a 5-point Likert scale*) and specific foods (*z=4.298, p=0.0001, 95%CI 0.418-1.470 higher on a 5-point Likert scale*) than people with casual goals, while no significant difference was observed among participants with different goals for other prompts. Qualitative results showed that participants with awareness goals usually preferred notifications that reminded people to manually journal food: *"If it is asking me to manually type information, I will remember that better"* (P48). People with awareness goals often preferred to enter information themselves. For example, some participants who were confident in their memories felt a reminder was enough: *"Just reminders would be helpful - I don't forget what I just ate"* (P15). Aligned with studies on semi-automated tracking [19, 49], some participants preferred a reminder to manually journal because it could prevent ADM sensors from incorrectly identifying what they ate: *"reminding me to manually log if the tracker didn't recognize would be very helpful"* (P73). Participants with numeric counting or nutrient-related goals cared whether prompts could provide *"nutritional or caloric content"* (P298). For example, people with weight management goals would particularly want to *"receive alerts if the food [I] just ate would include the types of calories (fat, protein, carbohydrates) and gave me a warning that [I] had just eaten too much fat or carb limit for the day or am close to it"* (P267) . Participants were generally more interested in on-body ADM sensors that could provide "what" people eat than "when" people eat: *"Less since I do not track when I eat, but rather what I eat. The trackers with image capabilities I would use"* (S11). Therefore, participants with health goals, such as healthy eating and managing diseases, preferred prompts that contained specific food information or food groups since they could either provide nutritional information or calculate food calories: *"I would be willing to receive information about the food group. For instance, is it protein, vegetable, iron etc. This is to help me know if I am eating a balance[d] diet or not"* (P142). P156 felt monitoring food for specific health conditions would benefit from having as detailed food information as possible: *"Food information in details, especially for allergy reasons. Knowing what exactly you eat is important."*

Many participants were not as interested in receiving food texture or audio clips, since they doubted that this information would be useful for their food journaling goals. For example, P20 wondered how audio clips would work: *"I don't understand what the audio clip would be. Is it the sound of me eating? Or am I leaving an audio message to myself stating what I ordered? The later [sic] would be more helpful."* Participants also felt that listening back to their chewing sounds could be uncomfortable: *"I do not like the sound of eating or chewing it would take a toll on me"* (P9). Participants felt it would be difficult to recall food just based on its texture, as many foods have similar textures: *"Info about texture would also have a mental burden because many different foods could have a crunchy or soft texture"* (P39), and even the same ingredient could be cooked to have different texture: *"I'm not sold on the 'texture' as a reliable app feature because one type of food can be cooked in so many different ways that its texture can change"* (P41). P10 even felt recalling these sensations could be torturous for people whose goal was to control diet: *"When you're dieting, the last thing you want to have to do is discuss further the texture or taste of the food, much less have to enter details about the sounds of the restaurant."*

4.2.2 Visual and Specific Information can Aid in Recollection and Reduce Time Burden. Participants felt that prompts with more specific food information, such as images of the foods they ate and the names of detected foods, would lower recall burdens and improve accuracy of recollected data. Participants anticipated that it would be easier to remember what they ate when prompts contained specific foods (*$z=9.784$, $p<0.0001$, 95%CI 0.70582-1.2270 higher on a 5-point Likert scale*), food groups (*$z=4.714$, $p<0.0001$, 95%CI 0.19984-0.7079 higher on a 5-point Likert scale*), food pictures or videos (*$z=3.139$, $p<0.0001$, 95%CI 0.04945-0.5704 higher on a 5-point Likert scale*) than other information. Participants felt visual information could offer a direct *"sensory stimulation"* (P22) and support more accurate entry: *" the visual devices would allow you to see / the device to "see" what is being ingested for tracking"* (S34). Participants similarly preferred prompts which contained specific food because *"The more specific the information is, the more likely I will be able to recall the food I ate"* (P39).

Participants anticipated a few different time burdens around responding to food journaling prompts, leading to being more willing to receive prompts containing visual and specific information. First, some prompts that contained no or less food information would demand more manual effort to journal. For example, P144 envisioned that it would be burdensome to manually add food information if only given the reminder to log: *"Manually logging would take up the most time because every decision is up to you. Whether it be what kind of food or how much of it, all of those decisions are coming from your information rather than help from the tracker."* Second, participants felt that prompts containing information which was not glanceable would also increase time burdens: *"I would be distracted and bothered by notifications that included audio or video of food, anything that required more than a quick glance while doing some other activity and needed me to perform another action"* (P100). Participants also felt ambiguous information, such as food texture, would also require more time to process: *"Vague information about texture and audio information would require more time away from social activities"* (P178). Third, prompts which contained too much information could also create time burdens. For example, P231 complained: *"I just need a reminder of what I ate, not a dissertation detailing exactly how and in minute detail (so no need for videos, audios, and texture. that's just TMI to me)."*

4.3 RQ3: When People are Most Willing to Respond to a Food Journaling Prompt

Participants were more willing to receive prompts either a short time after eating (*$Z=9.755$, $P<0.0001$, 95%CI 0.717-1.231 higher on a 5-point Likert scale*) or at a time they set themselves (*$Z=7.036$, $P<0.0001$, 95%CI 0.449-0.969 higher on a 5-point Likert scale*) than one hour after eating, while eating, and a long time after eating (e.g., two or three hours) (Figure 4 B). Participants with health or weight goals tended to have stronger preferences about when to receive prompts than participants with casual goals. Participants with health or weight goals were more willing to receive prompts either a short time after eating or at the time set themselves than other timings (*$z=12.895$, $p<0.0001$, 95%CI 0.572-0.812 higher on a 5-point Likert scale*). However, we observed no significant difference in preference among the different timings for participants with casual goals (*p=0.100*). Participants preferred to receive prompts shortly after eating for accuracy when their motivation and memory of journaling food were still fresh. Participants were also willing to receive prompts at the time set themselves to avoid prompts disrupting their everyday activities. Also, participants felt that prompts too frequently would increase interaction burdens for journaling food and even lead to negative attitudes about eating.

Aligning with prior work, participants preferred to receive manual journaling prompts sooner after eating rather than later, feeling their memory and motivation for reviewing prompts and manually journaling food would fade as time goes by [38]: *"logging immediately after eating makes the most sense to me. That way, the information is fresh, and I can remember specifics about how much and what kinds of foods I've eaten. [...]I worry if I wait too long, though, that I won't remember what I've eaten anymore - especially not how much"* (P52). In addition, some participants felt that notifications received not long after they ate would serve as a helpful reminder to add further details, especially for information that ADM sensors might be incapable of detecting. For example, P223 with healthy eating and weight management goals said: *"I need it [the prompt] as soon as possible so [I] can be sure to measure portion size."* However, some participants felt adding further food information while eating could cause inaccuracies because *"I wouldn't want a notification while I'm eating because I may not finish all my food at that time. Waiting about 10 minutes after would assure that I ate all the food I was going to eat"* (P115). Participants expressed concern that receiving prompts while or even shortly after eating would disrupt social eating. For example, P168 said: *"I wouldn't want to log too soon after a meal because that is when conversations are usually most engaging in social situations."* P133 similarly felt people might engage with other activities right after eating with others: *"[I] think because after we finish eating we are going to other places or immediately driving off and then we tend to forget certain detail."* Therefore, many participants preferred receiving prompts at rest time, especially at night: *"I'm too busy throughout the day to take time to journal. Most of my journaling is done at the end of the day"* (P83). Furthermore, considering the anticipated time burdens of responding to prompts, some participants were hesitant to receive *"constant reminders"* (P7) that would *"get very annoying/frustrating to be prompted so often"* (P10) since *"Some people eat more throughout the day, others only have three meals, but would it prompt you at every separate food item?"* (P10). Prior studies suggested that food journaling manually through apps can make people obsessed with journaling and controlling calories [26, 33, 53]. Participants similarly worried that frequent prompts would increase the mental burden of eating and reinforce negative attitudes around food, especially for people with weight management goals: *"I just worry that the constant notifications would get really annoying and potentially lead to an eating disorder. So I'm very unlikely to want any of them trying to get me to hyperfocus on food"* (P112). Some participants correspondingly felt prompts with visual and/or specific information could be received later to reduce interaction burdens: *"my memory [won't] be as accurate later in the day so the best results would be closest to the time [I] am eating. unless [I] took a picture of each thing in which case that would remind me. taking a picture and then logging later could be an alternative to logging as [I] am eating"* (P100).

5 DISCUSSION

Participants were primarily concerned with the anticipated physical, social, and privacy burdens of wearing on-body ADM sensors, since they could negatively impact their eating experience. Specifically, ADM sensors' locations and capture modalities appear to influence people's anticipated burden and acceptance of ADM sensors. Participants' food journaling goals influence their willingness to wear ADM sensors, and further qualitative results suggest that people with different goals weigh burdens differently. For example, participants with weight management goals are more concerned with potential social burdens, while participants journaling food for health more generally tended to anticipate fewer or no social burdens. Though current ADM technology can collect a variety of food-related information, our findings suggest people are more willing to receive prompts that contain information relevant to their food journaling goals, such as people with health-related or weight

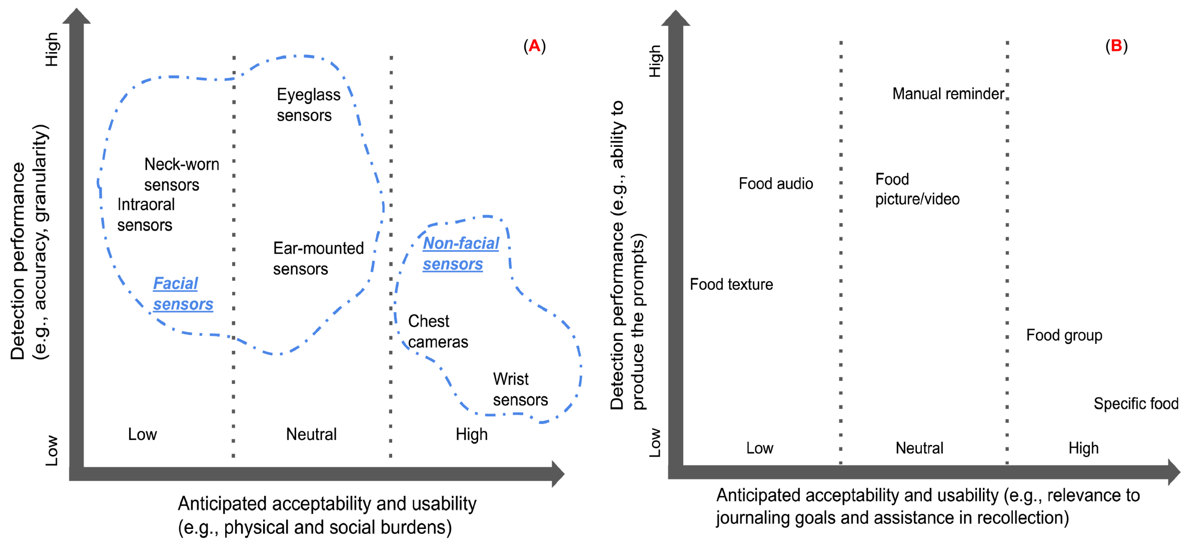

Fig. 5. Participants' preferences toward different on-body ADM sensors (A) and food journaling prompts (B) were compared against rough ability to detect the features as suggested by prior literature. The acceptability and usability of non-facial sensors like wrist sensors were well-regarded by participants, while their detection performance has often been lower than other approaches. Participants anticipated specific food information to have high acceptability and usability, but this information may be much more challenging to detect than other approaches.

goals being more interested in receiving caloric and nutritional information. Participants were more willing to receive prompts that would help them recall food information and take less time to respond to, ideally either shortly after they eat or at a time they set.

Our findings suggest somewhat of a tradeoff in the current design of ADM systems between detection performance and anticipated acceptability (Figure 5). Prior literature suggests that sensors placed on facial areas tend to have high detection performance (e.g., accuracy and granularity) [7]. However, participants generally anticipated lower acceptability and usability of facial sensors (e.g., intraoral, eye, and neck) than non-facial ones (e.g., wrist and chest) because of higher physical, social, and privacy burdens. Acceptability and usability were anticipated as high or neutral for prompts containing specific food information, food groups, food pictures or videos, or reminders to manually log food, as participants felt they would align with their food journaling goals and help them recollect food information. However, the ability to practically produce these prompts varies greatly. For example, systems levering complex algorithms to process real-time signals, such as images or videos, into specific foods take time and have accuracy limits [41, 70], while manual reminders and food pictures may be easier to immediately sent to people and be more accurate.

Our findings offer directions for researchers and practitioners improving ADM sensors' accuracy and privacy, and recommendations for improving acceptability of semi-automated food journaling systems.

5.1 Directions for Improving ADM Sensors' Accuracy and Privacy

While improving the accuracy of any ADM sensor will improve its utility, improving the accuracy of more acceptable, but less accurate ADM sensors (Figure 5 A) is a particularly valuable direction for future work. In particular, participants were overall more willing to wear wrist sensors with any detection modalities, suggesting the benefit of continued research on improving wrist-worn ADM sensors. In addition to body location impacting acceptability, our results suggest that the sensing modality influences people's anticipation of ADM systems. Participants' perspectives suggest the benefit of leveraging sensors that reveal less information about other aspects of people's everyday lives. Sensors producing less obviously human-interpretable signals, like accelerometers, appear more acceptable for ADM systems than ones which are, like microphones and cameras. Therefore, selectively choosing detection modality based on sensors' body locations can be one way to improve ADM systems' privacy. For example, participants associate sensors explicitly put in front of a person's body with the greatest privacy burden. Researchers and practitioners thus can consider only using the motion modality for people who prioritize privacy when wearing ADM sensors in front of their bodies. However, limitations in the detection capabilities of these approaches may trade off data quality to protect privacy.

Among more privacy-invasive approaches, participants sometimes expressed worries that ADM sensors may capture data irrelevant to the foods they ate, since ADM sensors may need to always be on to detect when a person is eating. Allowing people to manually activate ADM sensors when they wish to capture food-related information can help mitigate privacy burdens. Though having manual activation burdens, systems can still allow audio or image modalities to capture and process food information, lessening the entry burden more than a fully manual system. Semi-automated systems can also give visual indications that sensors are beginning to capture information since some participants worry ADM sensors would track data unnoticed.

A tension with approaches to lowering burdens to use of ADM sensors is that ADM sensors need to continue to add value beyond what manual food journaling can provide. In many ways, manually enabling and disabling collection with an ADM sensor inherits many of the limitations of manual journaling. People may just as easily forget to turn on the ADM sensor as write an entry in their manual journal, and people may not want to draw attention to their journaling in social settings. In addition, more acceptable prompts such as those containing specific food names or groups may require time to process or may not be able to be accurately and reliably produced. Many people wish to receive prompts shortly after eating for convenience and to assist with recall. Waiting for processing to occur, or correcting errors of lower-accuracy systems, may result in "smarter" prompting systems being less desirable than only detecting when a person is eating or manually scheduling prompts at a convenient time. In situations or circumstances where physical, privacy, social burdens are high, or where high accuracy is needed, it is worth considering whether the benefits of semi-automated journaling are sufficient to warrant using the approach over fully manual journaling.

5.2 Recommendations for Improving Acceptability of Semi-Automated Food Journaling Systems

5.2.1 Selecting Semi-Automated Approaches Based on Individual and Practitioner Needs. People's tracking and journaling goals and the interpersonal circumstances under which they collect data often influence selection among different digital tools [52]. Our work suggests that food journaling goals, presence or absence of social settings, and intended duration of use could all influence how people select different semi-automated approaches to food journaling.

Our findings suggest that people with health or weight goals prioritize entering more detailed food information, often preferring semi-automated systems that have greater detection performance. However, their goals lead to nuanced attitudes toward systems' anticipated social and physical burdens. Though tracking is often a collaborative and public practice [68], participants with weight-management goals often anticipate social burdens around ADM sensors, and they are reluctant to disclose their food journaling behaviors. Semi-automated systems for weight management should therefore particularly consider how systems' aesthetics and location on the body might impact perceptions [40, 61]. Placing on-body sensors in visually hidden locations or incorporating them into designs in forms similar to daily-worn accessories could help increase acceptability. Approaches with higher accuracy and lower social burdens, such as necklace- and eyeglass-shape sensors with image and/or sound modalities, could therefore be appropriate for people with weight goals.

In comparison, our findings suggest that people with more general health and wellbeing goals place no or less emphasis on the social burdens of ADM sensors, but instead need more flexibility around physical burdens depending on the health condition or need. When using technology to help manage chronic diet conditions such as diabetes or Irritable Bowel Syndrome (IBS), patients and providers often collaboratively make decisions about what data to journal, requiring patients to accurately monitor and share what they ate [4, 23, 40, 55]. Greater-accuracy, but lower acceptability approaches like facial ADM sensors with image and/or sound modalities could be valuable in these settings, as monitoring accuracy is of enough importance to warrant trading off some acceptability. However, the duration of diet monitoring can differ by chronic conditions, suggesting potential tradeoffs. For example, people with IBS often track food for short-term experimentation [23, 45, 72], which may align better with high-burden and high-accuracy approaches to ADM. Monitoring food for diabetes is often more passive and for long-term management of the condition [28, 60], suggesting that ADM approaches which are comfortable enough for long-term wearing may be more appropriate [40]. High-accuracy facial ADM sensors may therefore be less appropriate for diabetes monitoring. In addition, providers have different preferences regarding information type (e.g., specific foods and food groups) and data format (e.g., texts, audios, and images), with some data formats providing individual providers or providers focused on certain conditions more valuable information for providers to understand patients' conditions [4, 55]. For example, providers have found photo-based visualizations useful for understanding contextual information about eating patterns in IBS management, suggesting some potential benefit of that modality over others [23].

Moderate- or low-accuracy systems with high acceptability can assist people with casual goals or long-term goals in continual monitoring, and may be more viable for everyday use outside of clinical settings. Further, researchers aiming to conduct a long-term (e.g., multi-month) field study could employ sensors with high acceptability and moderate detection performance (e.g., ear-mounted sensors and chest cameras) to encourage longer-term wear. Prompting mechanisms can similarly trade off higher-acceptability for lower-performance, such as in prior studies aggregating prompts to be managed once per day [66]. These higher-acceptability, lower-accuracy approaches may also suit commercial systems, since lower-burden systems are often needed for sustained use and acceptability often drives adoption [82]. Higher-acceptability systems can also support people with casual food journaling goals, such as out of curiosity and a desire to keep a record of diet [35, 68], since these people may be less likely to tolerate the burdens of wearing ADM sensors and reacting to manual journaling prompts. Similar to how Apple Health automatically records and presents insights about people's physical activity to raise their health awareness, approaches with lightweight automatic detection of any aspect of eating patterns, such as when and how long people usually eat, can support curiosity and awareness. However, higher data granularity may be needed for certain goals, such as people journaling for diabetes monitoring or detecting food intolerances needing systems which allow for capturing nutrients like carbohybrates or fiber.

5.2.2 Selectively Presenting Food Information for Laypeople. This study surfaces a gap between what information on-body ADM sensors could theoretically detect versus what information people feel is relevant to food journaling. Though current studies show that ADM sensors can potentially detect data like food texture and specific food information [5, 7, 41, 70, 77, 79], our participants questioned some of these data's relevance or usefulness in helping them recall what they ate. We therefore suggest processing information into forms that elicit recall, rather than directly showing all the information that ADM sensors can capture. For example, participants often question the utility of food texture information. Beyond improving performance to infer food types based on food texture, prompts could provide contextualized examples of the textures of common foods. For example, if a short eating episode is detected, snack foods like chips for crunchy or fruits for soft foods could be suggested. Similarly, for people who dislike viewing food videos or images because of privacy or time concerns, systems can aim to process and summarize visual data into text descriptions which highlight potentially detected foods, such as specific food information or food groups.

5.2.3 Better Conveying Device Capabilities to Potential Users. Participants anticipated burdens of ADM sensors that may not come to light in practice based on the capabilities of ADM approaches. For example, participants sometimes questioned whether the motion modality may require them to make overly dramatic motions when they eat, and worried that on-body sensors may fall off the skin due to muscle movement from chewing or talking. We as researchers and practitioners have often accounted for these baseline concerns in the design of our ADM systems. However, people's anticipations influence whether they are willing to adopt a particular ADM approach, and therefore influence how we should design or message around these technologies if we want them to be used. Therefore, adequately describing device capabilities and limitations is crucial for advocating for semi-automated food journaling systems. For example, campaigns about semi-automated food journaling systems can show how wearers interact with devices in various scenarios to assuage people's concerns. Such campaigns can show people wearing facial sticker sensors on a hot sunny day or illustrate how motion sensors differentiate eating behaviors from other daily activities. Similarly, in clinical settings where a provider may require or suggest use of an ADM sensor, demonstrating how its capabilities can help allay concerns.

5.3 Limitations and Future Work

This study helps provide insight into how people might anticipate different sensors and prompting mechanisms, and how those anticipations might influence adoption. While our survey design was helpful for garnering initial impressions of a variety of different ADM and prompting approaches, other survey designs and other methods can further deepen our understanding. Splitting the survey to separately capture participants' anticipated preferences of ADM sensors and prompts helped ensure thoughtful response throughout, and under most circumstances perspectives are largely independent as detection and prompting occur on separate devices (e.g., on a mobile phone). However, some opportunities for ADM would benefit from understanding a more integrated perspective, such as understanding people's anticipations of notifications on the same wearable device where initial detection occurred, such as on a smartwatch or smart glasses. While fixing the order of ADM and prompting approaches allowed participants to readily compare among similar techniques, we acknowledge the potential for an ordering effect to influence participants' anticipated preferences. Randomizing order or asking more in-depth questions about a subset of ADM sensors and prompts will further validate anticipations. Because approaches to editing or manually logging food can reduce the relative burden of journaling [75], further surveying people's perspectives on logging mechanisms in conjunction with different types of prompts can further our understanding of how people anticipate approaches to semi-automated journaling. For example, future work could compare how people anticipate a diet app which asks for selection among potentially-detected foods with confirmation of the most likely detected food. Moreover, further research is needed to understand how people's anticipations are influenced by the use of these sensors and prompts in everyday life. Though we provided detailed descriptions and hi-fidelity sketches of each wearable ADM sensor and prompts, respondents' answers were mainly based on their imagination and previous related experiences instead of the real user experience. Further evaluations of novel ADM approaches in everyday life will help complement the perspectives offered by this study.

The survey method we leveraged in this work emphasized breadth over depth, readily enabling gathering perceptions of many semi-automated approaches. Collecting deeper understanding of people's attitudes toward semi-automated food journaling approaches would benefit from other HCI methods. Prior to developing a fully functional system, researchers could further evaluate potential directions proposed by this study via speculative design methods, such as Wizard-of-Oz [31, 47]. For example, researchers could elaborate on prior speculative studies of novel wearable devices [27, 31, 50, 64] to ask participants to wear non-functional ADM sensors with distinct form factors, such as facial sensors and chest cameras, to better understand how daily situations shape people's anticipated physical, social, and privacy burdens. Researchers could also simulate prompting approaches by monitoring participants when they eat in a lab study or remotely, sending prompts with different timings and levels of specificity to understand what and how a person eats would influence their acceptability of what and when to receive prompts.

We aimed to recruit a representative sample because demographic factors like socioeconomics and age impact people's access to both food and technology [24, 84], and anticipations of different devices [62]. However, in recruiting a sample which aligned more closely with the demographics of the U.S., we were unable to filter by people who did or did not have prior experience with food journaling. Some participants might have a very negative anticipation about the food journaling idea itself, leading to overall negative answers about wearable ADM sensors and prompting mechanisms. In addition, most of our participants were well-educated and high-income, which might influence their acceptability of the technology and minimize concerns around financial cost. Many of our participants had experiences with wrist-worn wearable technology, which may also lead to their more willingness of selecting wrist sensors in our survey. Future research is also needed to be conducted in different countries, since prior studies suggest cultural differences in people's anticipated social acceptability towards wearable technology [32, 64].

6 CONCLUSION

Our work suggests that location and sensing capability of ADM sensors impact people's anticipations of the technologies, with people generally finding sensors not on their face or which detect less obviously human-interpretable signals more acceptable. Wearing ADM sensors for continuous detection introduces physical and privacy burdens, while just wearing sensors while eating introduces social and interaction burdens. There is potentially a gap between what information ADM sensors are well-suited to detect and what information people find valuable in prompts or reminders, suggesting future research into processing signals into information that can aid with food recall. Improving the accuracy of more acceptable but less accurate sensors, selectively choosing detection modalities based on body locations, and allowing people to manually activate sensors can help make semi-automated food journaling a more viable approach.

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