Capturing Nutrition Data for Sports: Challenges and Ethical Issues

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Abstract. Nutrition plays a key role in an athlete's performance, health, and mental well-being. Capturing nutrition data is crucial for analyzing those relations and performing necessary interventions. Using traditional methods to capture long-term nutritional data requires intensive labor, and is prone to errors and biases. Artificial Intelligence (AI) methods can be used to remedy such problems by using Image-Based Dietary Assessment (IBDA) methods where athletes can take pictures of their food before consuming it. However, the current state of IBDA is not perfect. In this paper, we discuss the challenges faced in employing such methods to capture nutrition data. We also discuss ethical and legal issues that must be addressed before using these methods on a large scale.

Keywords: Nutrition · food images · privacy · AI · dietary assessment.

1 Introduction

Sports science, just like many other fields, has benefited from data-based research and advanced computing applications. Athletes are interesting subjects to study for nutritionists, sports scientists, doctors, and researchers from many more fields. Nutrition plays an important role in an athlete's performance and health [8]. Some nutrients, such as amino acid-electrolyte, can affect performance in endurance athletes [38]. Such effects of nutrition on performance can be applicable to the general population as well. In some cases, however, researchers discover placebo effects, such as that of electrolytes [23]; or refute old notions, for example, that athletic performance requires a diet high in proteins.

Research in sports sciences has focused on improving athletic performance, game strategies, and optimizing training processes. Body-worn sensors, such as ZXY sport tracking [28], capture an athlete's movements during a game. Other body-worn sensors, such as smart watches, can capture a multitude of individual performance indicators, on and off the field. However, smartwatches are targeted more toward individuals than teams. A combination of sensors with advanced video-based systems [15] can digitize gameplays and offer stakeholders analytical tools to improve game strategies. Looking at individual athletes, nutrition plays an important role in their performance. However, researchers have also discovered effects of an athlete's nutrition on other aspects beyond their athletic performance. Diets can be linked to an athlete's mood [36], behavior [19], and even mental well-being [22,30].

The robustness of nutrition research relies on the validity and reliability of the chosen dietary assessment method [20]. Capturing an individual's diet is challenging [7,20]. Most studies have relied on self-report methods to capture dietary intakes [20]. Self-report methods either rely on real-time recording or methods of recall [26]. Real-time recording methods, for example, food diaries require an individual to record every food or beverage they consume in real-time. Such methods are considered to be labor-intensive. The methods of recall (e.g. 24-hour dietary recall) rely on an individual's self-assessment of their diet. In 24-hour dietary recall, an individual is asked to describe the food they consumed over one day. Self-report methods (e.g., food records) are frequently utilized despite the evident inaccuracy of these methods in assessing energy and nutrient intake [12,37]. Memory-based methods are flawed with inaccuracies and depend heavily on the subjects' ability to recall their diet from their memory. Subar et al. [37] argue that despite the inaccuracies, self-reported data can be used to inform dietary guidance and public health policy. However, in sports sciences, as the focus is on personalized dietary interventions for athletes, the accuracy of dietary intake assessment methods is crucial.

IBDA methods that assess food intake via images of foods have overcome many of the limitations of traditional self-report. Taking images using a smartphone camera is less labor intensive than noting down food in a food diary. Deep learning methods and Artificial Intelligence (AI) can identify food from images taken with a smartphone camera [18,21]. In a lab, such as a cafeteria setting, digital photography has proven to be an unobtrusive and accurate method for assessing food provision, plate waste, and food intake. Many feasibility studies [4,16,25,29] have shown promise in using Image-Based Dietary Assessment (IBDA) methods for capturing nutrition data. However, state-of-the-art IBDA methods are not precise enough to capture dietary information accurately in every possible scenario. In their review, Höchsmann and Martin [16] highlight the benefits of taking food images over traditional dietary assessment methods, such as food records. They report that the technology to recognize food and portion size correctly is still in its infancy but promises real-time feedback to the user, reduces biases, and increases the efficacy of dietary interventions. Inferences from one's dietary data can lead to discoveries that may benefit both the athlete and the team. Long-running epidemiological studies can also incorporate these methods to accurately capture, analyze, and validate the effects of dietary interventions in a population.

Individuals' perceptions of the sensitivity of their data and the necessary privacy protections can change over time [2,32]. Perceived infringements to privacy can result in a complete rejection of new technology even if they are not based on evidence [2]. It is therefore necessary to address and mitigate such risks by providing accountability and transparency in a new system. Wachter and Mittelstadt [40] argue that individuals have little control and oversight over how their personal data is used to draw inferences about them. And the inferences derived from one's data might be considered sensitive by the individual while the legal frameworks might not provide the necessary protections. Recent laws, such as the General Data Protection Regulation (GDPR), have been hailed as promising as they provide an individual (or a data subject) with rights to know about (Article 13-15), rectify (Article 16), delete (Article 17), object to (Article 21), or port (Article 20) personal data. However, these rights are significantly curtailed for inferences. The GDPR also provides insufficient protection against sensitive inferences (Article 9) or remedies to challenge inferences or important decisions based on them (Article 22(3)).

In the following paragraphs, we will introduce nutrition data, its relevance for dietary interventions, and methods for dietary assessments. We will present our findings on privacy perceptions of food images followed by inferences and sensitivity as reported by the participants. Later, we discuss our findings, their relevance to sports sciences, and our conclusion.

2 Background

Nutrition data has its use in many research fields. Large cohort population studies are a frequently used tool to investigate epidemics such as obesity, heart, and coronary disease, diabetes, and cancer. The most frequently used tools are based on self-reporting either through interviews, questionnaires, or combinations [7,20,37]. The goal is to quantify the health status of each individual as well as of the population as a whole. More precisely that means describing relevant health parameters in objective and quantifiable metrics including anthropometrics (height, weight, etc.), biochemistry, and clinical issues. In a hospital setting, data sources may include blood samples, DNA, x-ray images, EMG, ECG, blood oxygen (VO_2) uptake, body composition scans, and many more. Applying these methods to large population studies presents many challenges. It can be too expensive and too invasive to apply such methods preemptively to a population as a whole. Also, since most interventions include dietary adjustments, it is necessary to collect data on what people are eating and drinking. In epidemiology, this is usually called *dietary assessment*. Epidemiologists investigate patterns and causes of diseases and other outcomes that affect people. A dietary assessment provides key data for epidemiologists studying all topics connected to the food intake of both populations as a whole, and on the individual level. The same methods to collect data are used by researchers, who devise and suggest food and dietary policies for the public, sports nutritionists, who manage the diet of athletes, physicians helping the chronically ill manage their diet-related diseases, and individuals doing self-interventions for their own health development.

The classical methods used to perform dietary assessment are few but clearly defined, and have stayed largely unchanged since their inception [14]. Most existing methods for dietary assessment are based on self-reporting. A recognized shortcoming of self-reporting methods for dietary intake is that they tend to have a bias that weakens the quality of the data [31], and several studies have questioned the validity of data from such methods [42]. Types of bias range from errors in how well subjects remember what they ate, misreporting due to practicalities and required effort to report, to the unwillingness to share certain details of their diet. The resulting discrepancies may be very large [43]. In fact, data collected by the U.S. National Health and Nutrition Examination Survey (NHANES) in the period 1971–2010 are not physiologically plausible when compared to estimated total energy expenditure [3]. Many computer scientists have seen this as an opportunity to contribute to the development of technology-based scientific methods for dietary assessment. While the methods used in dietary science can be described as various forms of subjectively validated self-reporting, methods developed in computer science are typically based on objective measurements from validated devices and sensors. A wide array of methods and technologies have been developed, but none of these seem to have gained enough traction to replace the standard methods of self-reporting in epidemiology.

Work done in this field is published in a wide array of publications, including dietary science, healthcare technology, bio-engineering, sensor, computer vision, and multimedia journals. Two previous surveys focused on studies on just one method, image-based dietary intake reporting [6,13]. These surveys are published in dietary science journals, and both compared studies gathered solely from medical and dietary publications. They also both compared effort and precision in these studies, with traditional methods as a reference. A third previous survey did a systematic review across multiple technologies, made a taxonomy to classify and describe the different technologies, but focused on readiness to deploy in low-income countries and published in a biology journal [9]. A fourth, earlier survey covered a broad set of technologies from an epidemiological perspective [17], but did not go into detail on each method, nor did it develop a taxonomy to describe them. Its focus was on how new technologies could be used in epidemiological studies. Finally, Public Health Nutrition [1] collected eight articles on automated dietary assessment as proof of the interest in methods and approaches that can be used for the automated collection and processing of data on dietary intake. The stated intent by its editor was to illustrate the width and the scope of current research efforts, but only the editorial mentioned all the specialized hardware solutions that are under development [24].

Dietary assessment is a complicated task that aims to quantify one's diet [7]. Surveys of developments in dietary assessments [6,10,16] highlight the importance of issues and the promise to mitigate some of them. Nutritionists and epidemiologists still use methods with a lot of participant and researcher burden [10]. Newer technological advancements are often ignored or disqualified due to a lack of acceptance in the community. Measurement errors in self-report dietary assessment methods [12,20] in epidemiological studies can be ignored due to large-scale data collection [37] as researchers are still able to use self-report methods for statistical analysis among a large population. However, in sports, personalized interventions are necessary. The same methods cannot be applied to the relatively small number of participants in athletic teams. Thus, to improve data collection and analysis, newer computer-assisted methods are being designed to improve the ease and accuracy of nutrition data collection and analysis. IBDA is one such promising method.

Computer-assisted methods are designed to reduce the labor required by participants and researchers. Some of these methods are very intuitive and embrace ubiquitous tools such as mobile phones. Once trained, these methods allow participants to conduct these assessments for a long time without needing supervision. Intuitive and easy-to-use tools are required in order to capture more nutrition data among participants. Such tools become necessary as more data is needed for personalized dietary interventions, which are more effective than general population recommendations [27]. Some of these newer tools may be perceived as intrusive by the participants. Participation in research studies relies heavily on trust, and any damage to their reputation can have severe consequences for organizations that obtain data based on informed consent. Thus, it is crucial to understand challenges and ethical issues before implementing and using new tools for capturing data. In the next Section, we describe a study in which we investigated some of these challenges.

3 Our Experiences with Privacy Perceptions of Food Images

We investigated common perceptions of computer systems using food images for dietary assessment. The study also delves into perceived risks and data-sharing behaviors. In the study [32], we investigated the privacy perceptions of 105 individuals by using a web-based survey. We analyzed these perceptions along with perceived risks in sharing dietary information with third parties.

We conducted the study by using a web-based questionnaire. The questionnaire was developed using close-ended questions for their statistical analyses. Some questions are repeated in the questionnaire to reduce biased context. Responses were collected between February and June 2019. The survey was designed to record participants' perceptions in the following scenarios: (1) Scenario A, the participant having to record and share dietary data as an athlete; (2) Scenario B, the possibility and severity of privacy leak from one's dietary data; and (3) Scenario C, sharing dietary data and reports among different social groups. We analyzed the data and performed P-value checks for hypotheses testing.

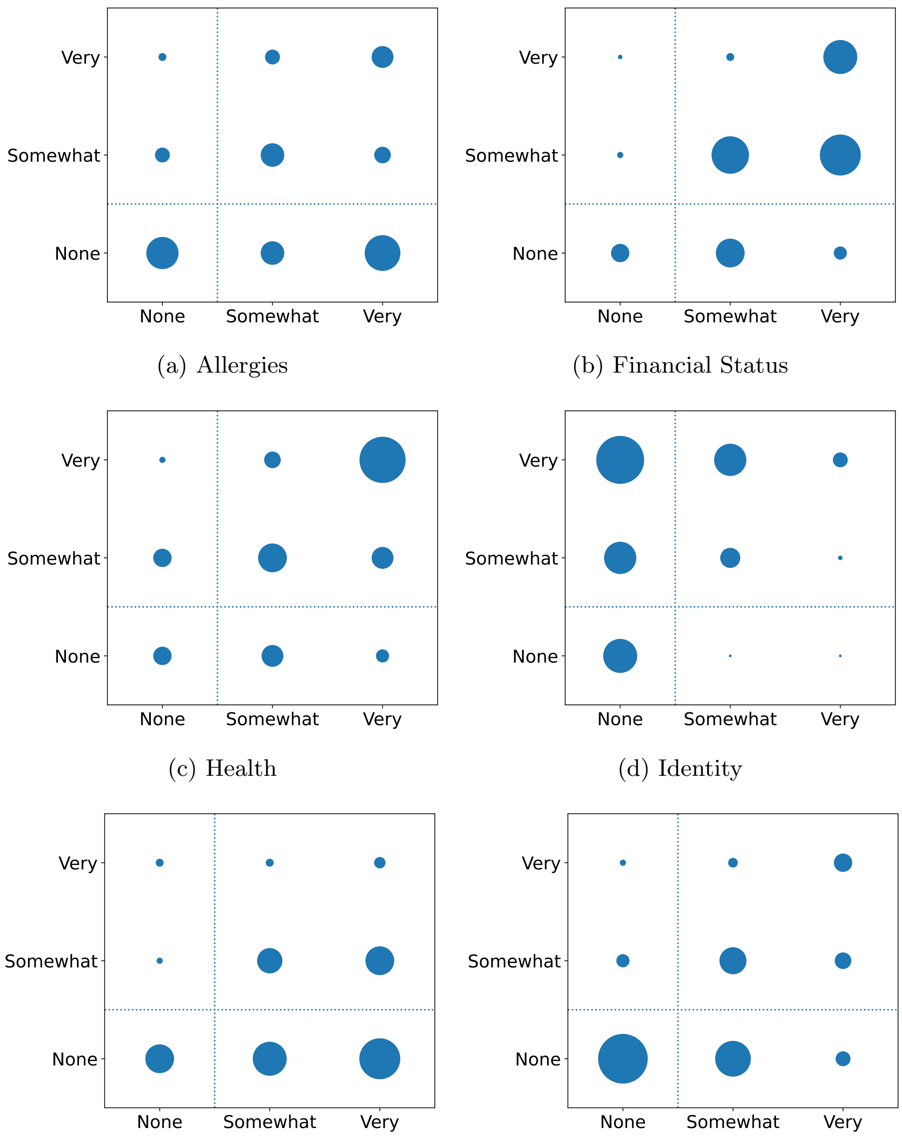
We now present a brief summary of the results. One of the goals of computer-assisted methods is to reduce labor. In terms of effort, approximately 80.9% (85/105) of the participants agreed that capturing diet records by using a phone camera is easier than writing down their dietary intake. Similar to writing down, individuals can also record audio to describe their diets accurately to record them. However, more than four-fifths of the participants (86/105, 81.9%) preferred capturing photos over recording their diets by voice. Only some participants were undecided about preferring image capture over writing down or recording audio (7/105, 6.7% and 8/105, 7.6%; respectively). Overall, the IBDA method seems to be the preferred self-report method for dietary assessment by the participants.

People take pictures and share them with their social groups through different channels. We investigate the sharing behavior in the context of food images. Taking a food picture and sharing it is considered as a familiar practice among the general population. About half of the participants (52/105, 49.6%) had previously posted food images on social networks. Even those participants, who lacked experience (53/105, 50.4%) in posting food images, showed similar attitudes toward the ease of recording their diet intakes by using photography. For a successful IBDA-based study, a participant must record every dietary intake whether a meal or a beverage. Compared to the irregular posting of images on social networks, adherence to recording diets requires extra effort from a participant. Some may perceive it as intrusive. When we asked about the intrusiveness of such a requirement, about two-thirds of the participants (69/105, 65.7%) indicated that it would be intrusive.

In terms of sharing behavior, participants reported varied preferences depending on the context of the metadata. When done in real-time, recording a diet can generate metadata such as time and location from a smartphone. We asked participants to report their preferences on sharing such metadata with their different social groups. We used *Family*, *Friends*, *Doctor*, *Team*, and *Fans* as the target social groups, as they would be relevant for an athlete. In comparison to the social group family(79/105, 75.2%), the participants were more willing to share food images with their doctors (94/105, 89.5%). Only a quarter (26/105, 24.8%) of the participants showed a willingness to share food pictures with their sports team while nearly half (47/105, 44.8%) showed a willingness to share food pictures with friends. In terms of the metadata associated with dietary data, the willingness to share drops further. Only 68.6% (72/105) of the participants agreed to share the time of the meal with their families in comparison to 82.9% (87/105) sharing the time of the meal with their doctors. The time of a meal is in fact an important consideration for elite athletes and their coaches for restitution and training planning. The full analysis can be referred to in our paper [32].

4 Inferences and Sensitivity

The state of AI-based inferences from food images is still in its infancy [16]. Researchers are exploring novel methods to extract, analyze, and infer useful information from food images [6,10]. There might be some information about the participant that can be inferred from their food images, which the subjects did not consent to. Such inferences can be perceived as privacy infringements by the participants and affect the perception towards the use of IBDA methods. As noted earlier, perceived infringements on privacy can affect how users may adopt new technology [2]. Based on the data collected in our study [32], we present what participants perceived as possible to infer from their food image dataset, which



(a) Allergies
(b) Financial Status
(c) Health
(d) Identity
(e) Nationality
(f) Religion

Fig. 1: Perceived *Likelihood* (x-axis) vs *Level of Concern* (y-axis) for different inferences from an individual's food image dataset as reported by participants (n=105).

has been anonymized. Additionally, they also indicate how sensitive they think such information is to them. The participants indicate their responses as *none*, *somewhat*, or *very* for both the likelihood and their level of concern. We plot the graphs based on responses from the participants (n=105). The attributes that are concerning to the participants will be indicated by the size of bubbles above the dotted blue line. Similarly, the attributes, which the participants think can be derived from their food images, will be indicated by the size of bubbles on the right side of the blue-dotted line. The participants were not given any scientific input on the current state of the research. The results are purely based on their knowledge and thinking.

Figure 1 shows the *Likelihood* and the *Level of Concern* if information about an individual can be inferred from their food image dataset. Note that these perceptions about the likelihood of inference might not be based on reality but perceived by the participants. However, we consider them as these perceptions may affect one's willingness to use IBDA methods to record their nutrition data. In Figure 1a, the participants report that it might be possible to infer their allergies from food images. However, they do not seem to be very concerned about such information. It may be that they perceive allergy information as useful for dietary interventions for recommending a better diet. The possibility of deriving one's financial status (Figure 1b) from their food image seems concerning to the participants. And they report that it is likely to be derived from the images.

Additionally, health information (Figure 1c) is another area where participants report a higher level of concern if inferred from their food dataset. The perceived likelihood of such inference is also high among the participants. The participants do not believe that one's identity (Figure 1d) can be inferred from their food image dataset. However, the level of concern about one's identity is high, which is in line with earlier research [5,41]. Inferring one's nationality (Figure 1e) or religion (Figure 1f) is not as concerning as one might believe. However, in cases of discrimination, these might be protected under the law. Participants reported that it is very likely that an individual's nationality can be inferred from their food image dataset. They also reported that it is not very concerning to derive one's religion from their food dataset. However, only 16% (17/105) of the participants reported following a religious diet.

5 Discussion

Nutrition data allow researchers to understand novel relations between our food and its effect on our bodies. The research's impact is beyond the field of sports sciences. Traditional methods suffer from limitations that restrict nutrition data collection on a larger scale, outside a lab, and in longer temporal periods for longitudinal studies. Novel computer-assisted methods to capture nutrition data provide a good opportunity to increase the scale of the research. Combined with deep learning and AI, and the increasing scale of nutrition research, personalized dietary interventions can benefit from evidence-based insights impacting healthy developments. The fields of sports sciences, epidemiology, and nutrition will benefit from precise, non-biased, large-scale nutrition data collection. As it is with other fields, the challenges and ethical issues need to be addressed as well.

IBDA-based methods provide a scalable solution to capture nutrition data. As reported in our study [32], taking photos of food as a method to self-report diet is preferred over other traditional methods. It still requires some labor on the participant's part to take the picture. Passive video surveillance methods to capture nutrition using video cameras in a canteen (or a lab) can reduce the participant's labor further. However, the privacy implications and the required GDPR consent can become a challenge [11] as individuals need to give their explicit consent. The collected nutrition data can be useful for nutritionists, doctors, and researchers. Sharing of such data requires consent from the participants as they might be continuously adding more data for personalized dietary interventions. In our study [32], individuals reported varying behaviors for sharing data, as knowing what the data is being used for increases the chance of it being shared. No single policy can be applied to indicate their sharing preferences for all users as the perception of their privacy and their sharing behavior can be highly variable.

People's perception of their privacy evolves over time [39]. And so does their perception of what is possible to infer from their data. Their perceptions may change over time due to knowledge or growing coverage of privacy issues in the media. As the sensitivity of the inference changes, a participant's consent to sharing may change as well. GDPR and other modern laws provide subjects/participants with extended rights to their data. Existing role-based access control systems for sharing the data may result in a one-time-only check for data access. Furthermore, the sensitivity of one's information is also not static. System support for managing sensitivity and evolving perceptions requires dynamic policies that are attached to the data and not the system. Such a system should also be able to handle accountability to provide subjects with information about the data being used. For sports science, a large amount of athlete data collected on and off the field presents a big challenge of data ownership and privacy concerns [35]. Such a system can be crucial in sports where athletes' participation is crucial and relies on their trust in the team and institution.

We have built *Lohpi* [33,34], a distributed system to support dynamic policies. We argue for a decentralized approach, where different institutions can process data on their infrastructures and maintain control of data assets, rather than a central one-fits-all service. The policy enforcement is done at the nodes hosting data assets and updated through a resilient metadata distribution substrate. The metadata distribution substrate is implemented using gossip-based data exchanges, which is a probabilistic data dissemination scheme. We have primarily used it in the medical domain, but also for sharing soccer data from female top athletes in Norway. Privacy and security have been first-order design principles, and the system can easily be adapted to support nutrition data (both media files and extracted information). Notably, this system enables sensitive data to be shared between collaborators in a controlled manner. We argue that a decentralized service that maintains metadata, a global view of all data usage, and active policies combined with local monitoring and security enforcement can provide automated compliance checking.

6 Conclusion

Taking food images is an interesting method for capturing nutrition data. It potentially requires much less labor when compared to traditional dietary assessment methods, and almost no training as individuals are already familiar with capturing images with their smartphones. The captured data can be fed to AI-based systems that can provide real-time dietary interventions toward a specified goal. Such systems present interesting opportunities for sports where stakeholders (coaches, managers, and owners) are interested in improving athletes' performance, maintaining good health, and their mental well-being.

We presented our findings on perceptions towards capturing nutrition data using food pictures. These perceptions play a vital role in the acceptance of new technology. Any perceived risk or sensitive information must be handled carefully with accountability and transparency in the system. New laws and regulations can also introduce changes to an information's sensitivity. A system must support these changing perceptions and information sensitivity.

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