VTT Technical Research Centre of Finland

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Published in:
Trends in Food Science and Technology

DOI:
10.1016/j.tifs.2022.05.006

Published: 01/07/2022

Document Version
Publisher's final version

Trends in Food Science & Technology 125 (2022) 100–113

Contents lists available at ScienceDirect

Trends in Food Science & Technology

journal homepage: www.elsevier.com/locate/tifs

Overview of objective measurement technologies for nutrition research, food-related consumer and marketing research

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ARTICLE INFO

Keywords:
Objective measurement
Emotion
Eating behaviour
Food choice
Food intake

ABSTRACT

Background: Despite their reliability- and validity-related challenges, self-reports remain the most common data collection method in nutrition research, food-related consumer and marketing research. The rapid development of technology has nevertheless inspired attempts to overcome the challenges of self-reports by applying technological solutions capable of capturing objective data.

Scope and approach: We reviewed objective measurement technologies applicable in nutrition research, food-related consumer and marketing research, spanning the continuum from food-evoked emotions to food choice and dietary intake. Focusing on non-invasive solutions, we categorised identified technologies according to five study domains: 1) detecting food-related emotions, 2) monitoring food choices, 3) detecting eating actions, 4) identifying the type of food consumed, and 5) estimating the amount of food consumed. Additionally, we considered technologies not yet applied in the targeted research disciplines but worth considering in future research.

Key findings and conclusions: Within each domain, several variables have been measured using diverse technologies or combinations of technologies. These technologies cover wearable and remotely applied solutions that collect data on the individual or provide indirect information on consumers' food choices or dietary intake. The key challenges of the reviewed technologies concern their applicability in real-world settings; capabilities to produce accurate, reliable, and meaningful data with reasonable resources; participant burden, and privacy protection. We provide recommendations for researchers and practitioners in nutrition research, food-related consumer and marketing research to work around the key challenges. For fruitful use of available technologies, we encourage collaboration between technology developers and experts in nutrition, consumer, and marketing sciences.

1. Introduction

"If consumers do not even know why they are deciding the way they decide, how could they give accurate answers about the motives for their behavior?" This citation by Danner et al. (2014, p. 167) captures well the essence of methodological challenges in behavioural sciences that conventionally rely on individuals' self-reports, such as interviews, questionnaires, and diaries. Similar challenges hold true in nutrition research and food-related consumer and marketing research, endangering the reliability, explanatory power, and predictive validity of research outcomes (Ahn & Picard, 2014; Garcia-Burgos & Zamora, 2013). At worst, inaccurate research evidence could misguide food development, clinical practices, nutrition recommendations, and even political decision-making (Dhurandhar et al., 2015).

Self-reports rely on people's introspection and memories, and can merely reveal individuals' perceptions on what they do and how they feel. A major problem with self-reports is misreporting, which has been found to concern up to 75% of adults (Rennie et al., 2007). Misreporting dietary choices, behaviours, and intake can stem from numerous reasons. First, food choices and eating often occur automatically with little or no conscious reflection and driven by unnoticeable influences, such as subtle environmental cues, past experiences, or emotions (Dijksterhuis & Smith, 2005; Thomson & Coates, 2021). Relatedly, the frequency and volume of foods consumed are difficult to recall and estimate precisely (Thompson & Subar, 2017). Self-reports and response styles can also vary depending on individual factors, including demographic

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https://doi.org/10.1016/j.tifs.2022.05.006
Received 9 January 2022; Received in revised form 6 May 2022; Accepted 11 May 2022
Available online 15 May 2022

characteristics, such as gender, education, or cultural background (Grunert et al., 2014; Murakami & Livingstone, 2015; Previdelli et al., 2019), as well as psychological traits such as social desirability (Thompson & Subar, 2017). Furthermore, data collection with self-reporting methods tends to be burdening, particularly within the nutrition domain. Keeping a food diary, for example, requires substantial efforts, motivation, and literacy, which challenge comprehensive reporting, restrict eligible study populations, and limit data collection periods (Thompson & Subar, 2017).

Technological advancements, including various sensor- and image-based tools, have raised expectations for their potential to solve the problems inherent in self-reports (Zhao et al., 2021). Past ten to fifteen years have witnessed increasing research efforts to develop technological approaches feasible for nutrition research (for recent reviews, see, e.g., Bell et al., 2020; Doulah et al., 2019; and He et al., 2020) and for specific consumer- and marketing-research domains, such as food-evoked emotions (Kaneko et al., 2018) and food choice (Van Loo et al., 2018). However, evidence on the potential of these approaches appears contradictory. On one hand, novel measurement technologies hold promises to detect food purchase and eating behaviours and their drivers more objectively, accurately, comprehensively, and efficiently (Bell et al., 2020; Skinner et al., 2020; Zhao et al., 2021). Novel technologies might also prove less burdensome and more appealing to study participants (Eldridge et al., 2018; Höchsmann & Martin, 2020). On the other hand, available technologies have been deemed still nascent (Bell et al., 2020), largely bound to controlled laboratory settings (de Wijk & Noldus, 2021; Doulah et al., 2019; He et al., 2020; Selamat & Ali, 2020), difficult to interpret (Cardello & Jaeger, 2021; Pennanen et al., 2020), and insufficiently robust and accurate to meet scientific standards (Höchsmann & Martin, 2020; Selamat & Ali, 2020).

Due to the potential and rapid development of objective measurement technologies, this study aims to generate a state-of-the-art overview on advancements in the field. Focusing on non-invasive solutions, the paper introduces technologies currently in use or under development for future application in nutrition research and food-related consumer and marketing research, and discusses the capabilities and challenges of these technologies. The paper draws a holistic overview of the continuum from food-evoked emotions to food choice and dietary intake—domains relevant for multiple research disciplines focused on food and eating. Thus, the paper extends beyond recent reviews that have focused on questions relevant to nutrition research (e.g., Alshurafa et al., 2019; Bell et al., 2020; Skinner et al., 2020; Zhao et al., 2021), specific consumer- or marketing-research domains such as food-evoked emotions (Kaneko et al., 2018), or certain technological domains such as image-based methods (Ho et al., 2020; Höchsmann & Martin, 2020). Additionally, instead of portraying technology development for other technology developers (e.g., Lo et al., 2020a), the paper adopts a language inclusive of and scope relevant to nutrition, consumer, and marketing researchers and practitioners. Consequently, the paper supports these professionals in evaluating the feasibility and opportunities of a variety of technologies in enhancing the reliability, validity, and applicability of research outcomes.

The paper follows a structure whereby section two focuses on describing identified objective measurement technologies, their capabilities, and current applications in nutrition research and food-related consumer and marketing research. Additionally, section two portrays technologies not yet applied in the targeted research disciplines but that could be worth considering in future studies. Section three focuses on challenges related to the reviewed technologies, and section four suggests ways to work around the challenges. Section five concludes the work.

2. Objective measurements applicable in nutrition research, food-related consumer and marketing research

The technologies that this review covers are organised in five domains that span the continuum from food-evoked emotions to food choice and intake. The included domains focus on 1) measuring emotional responses to food or eating, 2) monitoring food choices, 3) detecting eating actions, 4) identifying the type of food consumed, and 5) assessing the amount of food consumed. The review is limited to non-invasive technologies that can be used outside clinical settings. Table 1 provides an overview of the technologies and the variables the technologies measure. Most of the technologies are wearable solutions that collect data on the surface of the body. Yet, the review covers also remotely applied objective measurement approaches that collect data on the individual or provide indirect information on consumers' food choices or dietary intake. Fig. 1 demonstrates the targets of technologies that collect data on the individual. At the end of the section, we touch upon technologies that have not yet been applied in nutrition research nor food-related consumer or marketing research but that could be worth considering in the future.

2.1. Food-related emotions

Foods can generate emotions whenever we encounter food- or eating-related cues: while viewing food advertisement, when grocery shopping, during food preparation, and over meals. Emotional responses have a crucial role in predicting consumers' food choices (Dalenberg et al., 2014) and the success of food products (Brouwer et al., 2017). Hence, emotion measurements can provide valuable information on consumers' evaluations of foods, and they can predict food choices more accurately than food liking alone (Cardello & Jaeger, 2021; Gutjar et al., 2014; Schouteten, 2021). Since food-elicited emotions tend to be fleeting and short in duration (Verduyn et al., 2011), objective measurement technologies could complement subjective methods (Cardello & Jaeger, 2021; de Wijk & Noldus, 2021). Used technologies have focused on facial expressions and psycho-physiological reactions.

Facial expressions result from the movement of facial muscles, and they can reveal diverse emotional states, such as happiness or anger (Danner et al., 2014; Horska et al., 2016). In addition, facial expressions allow the measurement of emotional valence, which denotes the intensity of emotions on a continuum from negative to positive (Ahn & Picard, 2014). Facial expressions have been measured with video and web cameras supported by face-reading analysis software (de Wijk et al., 2019; He et al., 2014; Horska et al., 2016; Mehta et al., 2021), and with electromyography (EMG) sensors that monitor muscle activity (e.g. Álvarez-Pato et al., 2020) (Table 1, Fig. 1).

Psycho-physiological reactions result from the activities of the autonomic nervous system (ANS) and the central nervous system (CNS). ANS measurements reflect physiological reactions that result from brain activity, and they serve as indications of arousal (Maccioni et al., 2019) and action readiness (de Wijk et al., 2014; de Wijk & Noldus, 2021). Additionally, these measurements can reveal consumers' unconscious emotional reactions (Kaneko et al., 2018) or momentary, fast, and spontaneous responses to foods (Pennanen et al., 2020). CNS measurements are applied to measure approach/withdrawal motivational tendencies, and they reflect the neuronal activity of the cortex—the surface layer of the brain.

ANS reactions include changes in heart rate, skin temperature, and skin conductance. Heart rate has been measured with electrocardiogram (ECG) electrodes on the chest (He et al., 2014) or on the chest and lower back (Pennanen et al., 2020) (Table 1, Fig. 1). An alternative method is a remote photoplethysmography (PPG) system that uses image sequences of human face to compute heart rate based on blood flow-induced changes in skin colour (de Wijk et al., 2019; Wei et al., 2013). Skin temperature has been measured with electrodes on the palm of the hand (He et al., 2014), and skin conductance with galvanic skin response (GSR) electrodes on fingertips (Maccioni et al., 2019) or on the palm of the hand (He et al., 2014). Measuring CNS reactions, in turn, is possible with electroencephalograph (EEG) electrodes on the scalp (Horska et al., 2016). EEG measurements have enabled the detection of engagement,

Table 1
Overview of the variables of interest, data collection modes (wearable vs. remote), data sources, and technologies used in objective measurement of food-related emotions, food choices, eating actions, and the type and amount of food consumed.

	Food-related emotions	Food choice	STUDY DOMAIN Eating actions	Food type	Food amount
Variables of interest	Type of emotion Valence of emotion Arousal Action readiness Approach motivation	Visual attention Purchased food products	Meal rhythm Meal duration Eating speed Eating gestures Bites Chews Swallows	Food category Food item	Food volume Food mass Energy content Nutrient content
Used data collection modes, data sources, and data collection technologies	Remote Facial expressions – Face-reading via video/web cameras – Electromyography (EMG) Heart rate (HR) – Photo-plethysmograph (PPG) Heart rate (HR) – Electrocardiogram (ECG) Skin temperature – Thermometer Skin conductance – Galvanic skin response (GSR) Brain activity – Electro-encephalograph (EEG)	Wearable or remote Eye movements – Eye tracking – Virtual reality (VR) headsets Remote – Customer loyalty card data – Sales data – Receipts – GPS coordinates – Ecological momentary assessment (EMA) tools	Wearable Motion – Accelerometer – Gyroscope – Magnetometer – Inertial measurement unit (IMU) Sound – Microphone Muscle contraction – Electromyography (EMG) – Bending sensor Mechanical strain/vibration – Piezoelectric sensor Bioelectrical impedance – Electroglottograph (EGG) Proximity – Optical proximity sensor – Radio frequency transmitter and receiver Blood flow – Photo-plethysmograph (PPG) Ambient light – Ambient light sensor Multi-sensor modalities – Varying sensor-combinations detecting motion, sound, mechanical strain/vibration, proximity, blood flow, and/or ambient light	Wearable or remote Image/video of food – Camera Wearable Motion – Accelerometer – Gyroscope – Magnetometer Sound – Microphone Mechanical strain/vibration – Piezoelectric sensor Multi-sensor modalities – Varying sensor-combinations detecting sound, mechanical strain, and/or motion Remote Image/video of food – Camera Food identification tags – Radio frequency sensor Cutlery actions – Force distribution sensor Food colour – Digital RGB colour light sensor Beverage radiation – Optical spectrometer Beverage acidity (pH) – Ion-selective electrodes Beverage salinity – Conductivity sensor	Wearable or remote Image/video of food – Camera – Depth camera Wearable Motion – Accelerometer – Gyroscope – Magnetometer Sound – Microphone Mechanical strain/vibration – Piezoelectric sensor Remote Food weight – Weight sensor – Force distribution sensor – Force-sensitive resistor

boredom, immediate agitation, irritation, frustration, and meditation (Horska et al., 2016), as well as approach motivation towards foods (Pennanen et al., 2020).

2.2. Food choice

Consumers make on average over 200 food choices per day (Wansink & Sobal, 2007). These choices determine what, when, and how much people eat (van Meer et al., 2016), and directly influence wellbeing and health (Lyerly & Reeve, 2015; Maugeri & Barchitta, 2019). Thus, understanding how people arrive at their food choices is crucial. Food choices can be studied objectively by measuring visual attention to foods, by collecting food transaction data, and via ecological momentary assessment (EMA) tools (Table 1, Fig. 1).

2.2.1. Measuring visual attention

Visual attention refers to the gaze (i.e., eye movements) of a person towards a particular item or a part of it. Food choices and visual attention to foods or food products are strongly related (Van Loo et al., 2018). Greater visual attention can reflect the attraction of targeted foods (Motoki et al., 2021) and predict subsequent food choices (e.g., Bialkova et al., 2020). In food-related consumer and marketing research, visual attention measurements have targeted gazes toward served foods (Puurtinen et al., 2021; Wang et al., 2018), food products (Gere et al., 2016; Melendrez-Ruiz et al., 2022; Yang et al., 2018), food packages (Siegrist et al., 2019), product labels (Fenko et al., 2018; Peschel et al., 2019) and other product information (Bialkova et al., 2020; Van Loo et al., 2021).

Eye-tracking technology enables the measurement of eye movements and provides an objective method for studying visual attention (Duchowski, 2017). Eye tracking is possible with remote and wearable eye trackers (e.g. Gere et al., 2016; Peschel et al., 2019). Remote eye trackers can be mounted on computer screens or placed between the participant and the screen, whereas wearable eye trackers can be embedded in specialised eyeglasses (e.g. Bialkova et al., 2020; Puurtinen et al., 2021; Siegrist et al., 2019; Yang et al., 2018). Recent wearable solutions include also Virtual Reality (VR) headsets with end-user hand-held controls (Melendrez-Ruiz et al., 2022; Siegrist et al., 2019). Eye trackers allow monitoring, for example, the fixations of eyes on particular food items or other Areas of Interest (AOI), such as labels or information on food products. Fixations are eye movements that stabilize the retina over a stationary object of interest, and they serve as proxies for the locations of the viewer's visual attention (Duchowski, 2017).

2.2.2. Collecting food transaction data

Sources of food transaction data include customer loyalty card databases (e.g., Konttinen et al., 2021; Vuorinen et al., 2020), sales data (e.g., Vanhatalo et al., 2022), and receipts collected from customers after purchases (e.g., Biswas & Szocs, 2019). Food transaction data reveal, for example, the time and place of purchases, the type and amount of

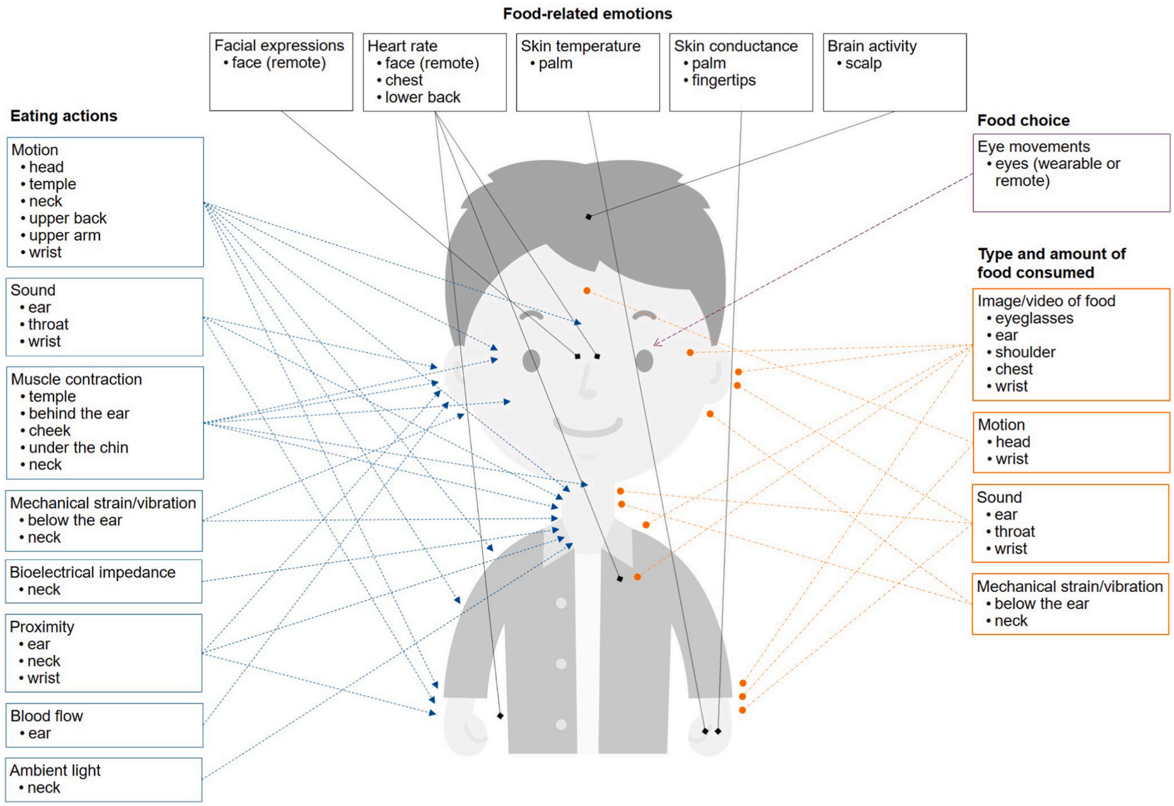

Fig. 1. Attachment of wearable technologies (and targets of remote technologies) used to collect objective data on individuals' food-related emotions, food choices, eating actions, and the type and amount of food consumed.

purchased products, and the amount of money spent on the products (Vanhatalo et al., 2022; Vuorinen et al., 2020). Customer loyalty card databases additionally enable connecting purchases with individuals or households, and tracking food purchases over longer periods.

Loyalty card data have been utilized for detecting socio-demographic differences in food purchases, for estimating the degree of customer loyalty to retailers, and for assessing the degree to which food purchase data reflects dietary intake (Konttinen et al., 2021; Vepsäläinen et al., 2021; Vuorinen et al., 2020). Sales data and customer receipts have been used for estimating the proportion of healthy and unhealthy food choices sold in lunch restaurants (Vanhatalo et al., 2022), and for collecting food choice and monetary data in retail settings (Biswas et al., 2019; Biswas & Szocs, 2019). In addition, customer receipts have been used in combination with wearable cameras that monitor customer purchases in supermarkets (Hui et al., 2013).

2.2.3. Ecological momentary assessment tools to record food choices

Ecological Momentary Assessment (EMA) tools work through smartphone applications and enable users to report subjective or objective data on food choices at the moment or right after food choices, hence limiting memory bias (e.g. Dao et al., 2021; Poelman et al., 2020; Widener et al., 2018). Reported objective data can involve text and images and portray, inter alia, receipts, prices, or types and amounts of chosen foods (Poelman et al., 2020; Widener et al., 2018). In addition, EMA tools can employ the global positioning system (GPS) to collect objective information on the location and time of food choices (Poelman et al., 2020; Widener et al., 2018).

2.3. Eating actions

Once food choices have been recorded, the first step towards objective and automated dietary intake assessment is to detect when people eat. Monitoring eating actions forms the foundation of a more fine-grained dietary assessment, such as the type and amount of food consumed (Bi et al., 2017), and can provide valuable information on individual eating habits, such as meal rhythm and duration (Blechert et al., 2017), as well as eating speed (Nicholls et al., 2019). Eating actions have been identified with wearable sensor technologies capable of detecting eating-related motion, sound, or muscle contraction, eating-induced mechanical vibration or strain, as well as changes in bioelectrical impedance, proximity, blood flow, or ambient light in the upper body area (Table 1, Fig. 1).

2.3.1. Sensing eating-related motion

Measuring movements characteristic to eating activities is an appealing approach to detect eating events, since many wearable commodity devices, such as smartwatches and activity trackers, embed motion sensors; making data collection feasible (Chun et al., 2018). Motion sensors comprise accelerometers, gyroscopes, and magnetometers, which measure acceleration, angular velocity, and magnetic field, respectively. These sensors can be used alone or combined, in which case the device is called an inertial measurement unit (IMU). Studies have measured eating-related motion by mounting sensors on wrists and/or upper arms to detect hand-to-mouth gestures (Amft & Tröster, 2008; Dong et al., 2014; Mirtchouk et al., 2016; Sen et al., 2017; Thomaz, Essa, & Abowd, 2015), on upper back (Amft & Tröster, 2008), head (Mirtchouk et al., 2016), or neck (Zhang, Zhao, et al., 2020) to detect upper-body movement during food intake, and on eyeglass temples to detect facial muscle activity during chewing (Farooq & Sazonov, 2018). Besides detecting eating events in general, motion sensors have also proved capable of distinguishing specific food-intake activities, such as eating solid food with fork and knife, fetching a glass and drinking from it, eating soup with spoon, and eating bread with one hand (Amft & Tröster, 2008).

2.3.2. Sensing eating-related sounds

Eating generates characteristic sounds that can be detected acoustically. Numerous studies have mounted microphones inside the ear to identify chewing sounds that travel from teeth and jawbone to the skull and ear canal (Amft & Tröster, 2008; Liu et al., 2012; Mirtchouk et al., 2016; Papapanagiotou et al., 2017; Päßler et al., 2012; Shuzo et al., 2010). In-ear microphones can also capture external eating-related sounds such as cutting food with a knife (Liu et al., 2012). An alternative and potentially more comfortable location for ear-mounted microphones is behind the ear, where the sensor does not block the ear nor impede hearing (Bi et al., 2017). A microphone on the throat, in turn, enables to capture swallowing sounds and to recognise eating episodes based on swallowing frequency (Makeyev et al., 2012). On the wrist, audio recorders can capture eating-related sounds from the surrounding environment, and can be employed to identify eating moments and their characteristics, for example, whether subjects eat alone or in company and whether the meal takes place in a restaurant or while working on the computer (Thomaz, Zhang, et al., 2015).

2.3.3. Sensing eating-related muscle contraction, mechanical strain or vibration

Muscle activity related to chewing and swallowing has been detected by attaching electromyography (EMG) electrodes to skin on various locations around the head and neck. Proposed locations include behind the ear (Bi et al., 2017; Blechert et al., 2017), on the cheek and under the chin (Nicholls et al., 2019), within a collar around the neck (Amft & Tröster, 2008), and on the temple of eyeglasses (Zhang & Amft, 2018). On eyeglass-temples, an alternative to EMG electrodes is a bending sensor (Doulah et al., 2021).

Chewing and swallowing induce mechanical strain and vibration as well, which can be identified with piezoelectric sensors. Attaching such sensors to skin below the ear enabled to measure chewing-induced changes in the distance between the jaw and skull bones (Sazonov & Fontana, 2012). Integrated into a necklace, in turn, the sensor allowed detecting swallows based on skin movement around the lower windpipe (i.e., trachea) (Kalantarian et al., 2014).

2.3.4. Sensing bioelectrical impedance, proximity, blood flow, or ambient light

Other innovative approaches for eating detection have relied on sensing bioelectrical impedance, proximity, blood flow, and ambient light. A collar with electroglottograph (EGG) electrodes at the level of the voicebox (i.e., larynx) detected swallows by measuring transverse electrical impedance across the neck (Farooq et al., 2014). Optical proximity sensors, in turn, were mounted on the ear to detect chewing-induced deformation of the ear canal (Bedri et al., 2015), and on a necklace to measure chewing-induced variations in the distance between the lower jaw and the base of the neck (Chun et al., 2018; Zhang, Zhao, et al., 2020). Alternatives to optical proximity sensors include radio frequency transmitters and receivers placed on the wrist and on a lanyard around the neck, respectively, to detect hand-to-mouth motion (Fontana et al., 2014). A photoplethysmography (PPG) sensor in the ear enabled chewing detection by optically measuring volumetric changes in blood flow (Papapanagiotou et al., 2017), whereas an ambient light sensor on the neck allowed detecting hand-to-mouth gestures (Zhang, Zhao, et al., 2020).

2.3.5. Multi-sensor modalities

Each sensor reacts to certain types of signals. Combining various sensors enables capturing diverse signals, which can be used to confirm or complement one another or to remove potential confounders, such as motion or sound unrelated to eating. Many studies have developed multi-sensor configurations to reach improved performance in detecting eating actions. Configurations that have outperformed single-sensor modalities have relied on, for example, sensing sound and motion (Mirtchouk et al., 2017); sound, blood flow, and motion (Papapanagiotou et al., 2017); sound and mechanical strain (Sazonov et al., 2009); mechanical strain or vibration and motion (Fontana et al., 2014; Kalantarian et al., 2015); as well as motion, proximity, and ambient light (Zhang, Zhao, et al., 2020).

2.4. Type of food consumed

Detecting eating actions can increase the understanding of individual eating behaviour. Diet-quality assessment, however, requires information on the types of foods and beverages individuals consume. Studies have proposed numerous approaches for technology-based or technology-assisted identification of foods. Some of these build on the same solutions that have been used in detecting eating actions (section 2.3). Proposed approaches involve image-based methods and wearable sensors sensitive to motion, sound, or mechanical strain or vibration (Table 1, Fig. 1). Alternatives to wearable solutions include sensors embedded in the food preparation or eating environment, or in cutlery.

2.4.1. Image-based methods

Capturing images or videos of consumed foods is an attractive approach to food-type identification. Data collection is convenient with widely available smartphones and wearable cameras, and can occur actively by the user or passively by the camera. Many smartphone applications represent active approaches, since they require users to take photos of all foods and beverages they consume (e.g., Nyström et al., 2016; Pendergast et al., 2017; Rollo et al., 2015). Passive solutions, in turn, often contain a wearable camera and a sensor module that detects the onset of eating, for example, based on chewing sounds (Liu et al., 2012), chewing-related muscle contraction (Doulah et al., 2021), or hand-to-mouth gestures (Sen et al., 2017), and consequently triggers the camera to capture images. Proposed locations for wearable cameras include chest (Sun et al., 2014), ear (Liu et al., 2012), wrist (Sen et al., 2017), shoulder (Qiu et al., 2020), and eyeglass frames (Chui et al., 2020; Doulah et al., 2021). Additional components such as GPS receivers can provide complementary data on eating contexts and available foods (Sun et al., 2014).

Besides data collection, also data analysis with image-based methods requires varying degrees of human input. In active methods, the analysis is fully dependent on human effort (Liu et al., 2012), and typically calls for trained nutrition professionals who assess dietary intake by reviewing photos taken by users (e.g., Nyström et al., 2016; Pendergast et al., 2017; Rollo et al., 2015). In such methods, food images serve as objective data on dietary intake, but their analysis relies on investigators' subjective evaluation. Automating image-based food identification requires advanced machine-learning methods capable of segmenting foods—i.e., identifying pixels in images that represent food—and consequently recognising the segmented foods (Alshurafa et al., 2019). In semi-automated solutions developed thus far, machine learning has assisted in filtering out irrelevant footage (Sen et al., 2017), in detecting food containers (Sun et al., 2014) and foods (Jia et al., 2019), as well as in classifying detected foods at a group level based on distinct features, such as food colour, texture, shape, or complexity (Chui et al., 2020; Kawano & Yanai, 2015; Sun et al., 2014).

2.4.2. Wearable sensor solutions

Wearable sensors that detect eating actions (section 2.3) enable food-type classification at a rough level. Eating-generated sounds, for example, provide an opportunity to classify foods based on sound characteristics dependent on food texture. Chewing and swallowing sounds have been recorded with microphones mounted on the ear (Amft & Tröster, 2009; Päßler et al., 2012; Shuzo et al., 2010), throat (Rahman et al., 2014; Yatani & Truong, 2012), and wrist (Kalantarian & Sarrafzadeh, 2015), and the recordings have been used to develop models for classifying foods among two to nineteen types (Amft & Tröster, 2009; Kalantarian & Sarrafzadeh, 2015; Päßler et al., 2012; Shuzo et al., 2010). These models have proved capable of identifying crispy foods, such as potato chips and carrots (Päßler & Fischer, 2014), as well as differentiating between eating and drinking (Rahman et al., 2014), between soft and hard foods (Shuzo et al., 2010; Yatani & Truong, 2012), and between sipping and gulping of beverages (Yatani & Truong, 2012).

Alternative to acoustic solutions, solid foods have been distinguished from liquids also with a neck-worn vibration sensor (Kalantarian et al., 2015) and with the combination of a strain sensor below the ear and a throat microphone (Sazonov et al., 2009). Data collected with the latter configuration additionally enabled defining the number of various foods in a meal based on distinct chewing and swallowing patterns that five diverse foods generated: pizza, yoghurt, apple, peanut-butter sandwich, and water (Lopez-Meyer et al., 2012).

Similar to the detection of eating actions (section 2.3), food-type identification too appears to benefit from multi-sensor configurations. One such solution comprised microphones in and outside the ear and motion sensors on head and on both wrists, and proved superior to simpler configurations in identifying foods among 40 diverse alternatives (Mirtchouk et al., 2016).

2.4.3. Sensors in the environment

In addition to wearable sensors, also the environment can feature technologies that assist in identifying consumed foods. Regarding food preparation and eating environments, examples include kitchens equipped with overhead cameras that allow tracking ingredients used in food preparation (Chi et al., 2008), and dining tables with radio frequency sensors that recognise foods by reading tags added to the bottom of food containers (Chang et al., 2006). Another example was a pressure-sensitive tray that could classify six types of foods based on distinct cutlery actions: stir, scoop, cut, poke, collect, and remove/replace (Zhou et al., 2015). In terms of cutlery and dishes, a colour-sensing fork embedded motion sensors that detected eating actions and a colour light sensor that identified food colour (Kadomura et al., 2014). For fluid intake monitoring, a cup was visioned that identifies beverages with a combination of an optical spectrometer, an ion-selective acidity (i.e., pH) sensor, and a conductivity (i.e., salinity) probe (Lester et al., 2010).

2.5. Amount of food consumed

While knowledge on the type of food consumed enables diet-quality assessment, estimating energy and nutrient intake requires also information on the amount consumed. Approaches developed for estimating the quantity of dietary intake have relied on capturing images and on wearable sensors sensitive to motion, sound, or mechanical strain or vibration (Table 1, Fig. 1). Additionally, some solutions have employed sensors in the food preparation or eating environment.

2.5.1. Image-based methods

Besides supporting food-type identification, images can also assist in assessing the amount of food consumed. As described in section 2.4.1, currently available image-based solutions require varying degrees of human input in data collection and analysis. Estimating consumption volumes often require that food images feature fiducial markers with known dimensions, such as standardised cards (Pendergast et al., 2017; Rollo et al., 2015) or checkered tablecloths (Nyström et al., 2016), which serve as geometrical references to the scale of the world coordinates (Xu et al., 2013). When human raters estimate consumption volumes, reference image libraries with pictures of various foods in different portion sizes support the estimation task (Nyström et al., 2016; Rollo et al., 2015).

Compared to the automated identification of eating actions and food type (sections 2.3 and 2.4), less research has focused on the automated estimation of the amount of food consumed (Mirtchouk et al., 2016). Yet, ongoing research keeps developing methods to produce three-dimensional (3D) reconstructions and volume estimates of foods that have been segmented and identified in images (e.g., Lo et al., 2020b; Makhsous et al., 2020; Sun et al., 2014; Xu et al., 2013). The volume estimates can be converted to weight, which allows computing nutritional content based on information retrieved from food-composition databases (Lo et al., 2020b; Makhsous et al., 2020; Sun et al., 2014). The 3D reconstructions can build on food scans captured with depth cameras or on regular photographs taken from one or more view angles (Lo et al., 2020a). The actual reconstruction can employ, inter alia, pre-constructed 3D models of common foods and/or deep learning methods (Lo et al., 2020a; 2020b).

2.5.2. Wearable sensor solutions

Similar to eating-action and food-type detection (sections 2.3 and 2.4), food-volume assessment too can benefit from sensor-based solutions. Wearable sensors have identified bites, chews, and/or swallows based on head and/or wrist motion (Mirtchouk et al., 2016; Scisco et al., 2014), based on eating-induced mechanical strain or vibration below the ear (Fontana et al., 2015) or on the neck (Kalantarian et al., 2014), and based on eating-related sounds on the ear (Amft et al., 2009; Mirtchouk et al., 2016) or on the throat (Fontana et al., 2015). Combining these data on eating actions with weighed mass of food consumed over a meal, experimental studies have demonstrated that bite count correlates with energy intake (Scisco et al., 2014), and that swallow count is associated with the amount of food consumed (Kalantarian et al., 2014). In addition, tracking bites, chews and/or swallows and corresponding weight of ingested food has enabled the development of mathematical models for predicting the energy value or amount of food consumed per intake and over an entire meal (Amft et al., 2009; Fontana et al., 2015; Mirtchouk et al., 2016; Salley et al., 2016). To obtain more accurate estimates of individual consumption, the models have additionally considered food type (Amft et al., 2009; Fontana et al., 2015; Mirtchouk et al., 2016) and individual characteristics, such as age, sex, and body weight (Salley et al., 2016), which might influence intake patterns.

2.5.3. Sensors in the environment

Besides wearable sensors, also food preparation and eating environments can collect data on the amount of food consumed. Coupled with technologies that identify ingredients used in food preparation and foods served over meals (section 2.4.3), weight sensors under kitchen counters, stoves, or table tops allow tracking the amount of food prepared and consumed (Chang et al., 2006; Chi et al., 2008). Another example was a tray that hid pressure sensors and that enabled predicting the amount of food consumed by tracking bites and the weight of food that disappeared from the plate with each bite (Zhou et al., 2015).

2.6. Other potential technologies for objective measurements in nutrition research, food-related consumer and marketing research

Certain technologies exist that are not yet applied in nutrition research nor food-related consumer or marketing research but that could be potential for these disciplines. Radar technologies have been successfully applied in monitoring heart rate and heart rate variability (Zhang, Li, et al., 2020), for example, when studying sleep quality (Turppa et al., 2020). These technologies are based on impulse radio ultrawideband radar (IR-UWB) (Zhang, Li, et al., 2020) or frequency-modulated continuous wave radar (FMCW) (Turppa et al., 2020). Both these radars allow remote monitoring of heart rate and heart rate variability—the very targets of psycho-physiological emotion measurements (section 2.1). However, unlike the psycho-physiological emotion measurements, radar technologies do not require the attachment of sensors to skin. This feature provides greater comfort to study participants. In addition, whilst currently applied objective emotion measurements are difficult to apply and thus limited to laboratory conditions, radar technologies could be used in more realistic settings. In retail environments, for example, radars could be attached to store shelves. It is unclear, however, how susceptible these measures are to confounding signals such as motion, and how to interpret obtained data.

Another potential, yet unapplied approach for real-time observation of consumers' food choices involves depth camera technologies. These technologies build on 3D situation-awareness data (Mäkelä et al., 2014) and utilise low-cost depth sensors that can be installed in various environments. The depth-camera approach enables the monitoring of space through several individual sensors that form a network that connects to a server and allows the processing of collected data into a global coordinate system (Vildjiounaute et al., 2017). The technology has been applied, for example, to monitor and analyse consumers' passage through retail space, and it has enabled the segmentation of retail patrons according to their movements and stops with 80% accuracy (Mäkelä et al., 2014). Compared to conventional video-based methods, the benefit of depth camera technologies is that they recognise shapes but cannot identify individuals under surveillance (Vildjiounaute et al., 2017). Hence, these technologies guarantee the privacy of observed study participants. Depth cameras could hold potential also in other purposes than monitoring consumers' passage through retail space. For instance, the sensors could be installed in store shelves or restaurant buffet lines to monitor hand movements and reaches that predict food choices. This could enable, for example, studying how food-package designs effect consumers' attention and consequent reaches to products in real-world retail and catering settings. Furthermore, combining the data on reaches with transaction data could enable the calculation of conversion rates from reaches to actual choices. An alternative to depth sensors to measure hand movements is low-powered thermal infra-red sensors (Alharbi et al., 2019). Compared to depth sensors, infra-red sensors are cheaper and consume less battery power, making them ideal for studies that last the whole day (Alharbi et al., 2019). However, the applicability of infra-red sensors in real-time studies is still under debate (Alharbi et al., 2019).

3. Challenges of objective measurements

3.1. Technologies for assessing eating-related emotions

The objective measurement of eating-related emotions has focused on facial expressions and psycho-physiological reactions; employing relatively mature technologies, such as web and video cameras coupled with tailored data-analysis software. Nevertheless, the role of objective measurements in emotion detection is considered technologically demanding and merely complementary to self-reports (Cardello & Jaeger, 2021; de Wijk et al., 2019; Schouteten, 2021).

The main challenges of objective emotion detection deal with feasibility, user comfort, and the accuracy and interpretation of produced data. Typically, data collection takes place in controlled study conditions that are unnatural and that can restrict the freedom of movement and cause discomfort for participants. Face reading, for example, may require participants to face the camera from a specific angle ($<40^{\circ}$) and to constantly look towards the camera when chewing or drinking (Danner et al., 2014). Psycho-physiological measurements, in turn, often require the attachment of electrodes to skin, for example, on the chest, palm, finger (de Wijk et al., 2014, 2019), or scalp (Horska et al., 2016; Pennanen et al., 2020). The feasibility of used technologies is hence limited, particularly in more realistic study conditions, and obtained results may translate poorly into real-world food-consumption situations (Cardello & Jaeger, 2021; de Wijk & Noldus, 2021). Due to the feasibility-related challenges, study samples remain small and may lack power to detect significant differences in measured variables even if differences truly exist (Mehta et al., 2021).

Regarding accuracy, a challenge related to facial-expression measurements is their capability to detect and discriminate between facial states. Confounders of accurate emotion detection include motor artefacts, because the analysis software can misinterpret eating and drinking as emotions (Danner et al., 2014). Another factor that appears to affect emotion detection and discrimination is the type of food samples used in experiments. Available technologies may be able to detect negative expressions that clearly disliked foods elicit (de Wijk et al., 2012), but fail to capture emotional responses to liquid samples such as drinks (Mehta et al., 2021). With samples from the same product category, technologies may be able to detect merely small, non-significant differences in emotional valence (Mehta et al., 2021).

Interpretation-related challenges concern particularly psycho-physiological emotion measurements. With these measurements, a key challenge is to interpret produced data meaningfully in the context of eating-related emotions, and to link the results to food preference and acceptance (Cardello & Jaeger, 2021; de Wijk & Noldus, 2021). For example, viewing a product can trigger detectable changes in skin conductance (i.e., galvanic skin response), thus demonstrating arousal, but the changed skin conductance does not reveal whether the reaction refers to a positive or negative emotional state (Maccioni et al., 2019). Another example relates to the relationship between heart-rate variability and food type and the moment of consumption (de Wijk et al., 2019). Variations in heart rate may reflect differences in emotional responses, but reported associations between heart-rate variability and food liking have been inconsistent (Brouwer et al., 2017; de Wijk et al., 2019). Another issue that hampers the interpretation of psycho-physiological emotion measurements is that emotional responses detected during eating can stem from a host of factors. Besides the foods and drinks consumed, such factors include the mental and physical state of the individual, time and location, social influences, other activities, and the recurrence of the eating event (Pennanen et al., 2020, de Wijk & Noldus, 2021). Therefore, detected emotional responses cannot be explained solely based on consumed foods or beverages or their properties.

3.2. Technologies for monitoring food choices

Technologies that allow collecting objective data on food choices include visual attention measurements with eye tracking, food transaction data, and ecological momentary assessment (EMA) tools. The main challenges with eye-tracking technologies concern feasibility, technological capabilities, the consistency of findings, and user familiarity with the technologies. Similar to emotion-detection technology (section 3.1), remote eye trackers are mostly used in sensory and eye-tracking laboratories in ways that restrict participant position and body movements. For example, eye trackers on computer screens require participants to constantly look at the screen while seated at a specific distance ($\sim$ 65 cm) from the screen (e.g. Van Loo et al., 2021). Such unnatural set-up challenges the real-life applicability and validity of study outcomes. Real food choices take place while standing and\or moving and while reaching for products at various distances. Wearable eye trackers solve the movement issue and enable eye-tracking experiments in more realistic food-choice settings (e.g., Bialkova et al., 2020; Fenko et al., 2018; Wang et al., 2018). The increased movement that wearable eye trackers allow may reduce measurement accuracy, however. Wearable eye trackers can easily lose track of participants' pupils when they look down (Puurtinen et al., 2021), and varying distances between participants and gazed objects may compromise calibration accuracy and reduce the reliability of results (Pérez-Edgar et al., 2020). Virtual reality (VR) technologies enable retaining the control that laboratory settings provide yet create a feel of real food-choice environments. VR-environments, however, can come with a host of stimuli that are unfamiliar to participants and that may hence distract participants from their assigned tasks (Siegrist et al., 2019), consequently biasing obtained results.

Although consumer and marketing research have applied eye-tracking technologies for decades, the interpretation of eye-tracking data remains a challenge. Whilst visual attention and food choices are strongly related (Van Loo et al., 2018), the relationship between gaze and choices is not straightforward. Recent evidence suggests that visual attention is positively correlated with food choices, but that the association may vary depending on factors, such as the gazed products, food choice motives and habits, and the difficulty of the choice task (Melendez-Ruiz et al., 2022; Motoki et al., 2021).

Regarding food transaction data, one of the challenges relates to linking food choices and the individuals who made the choices. This challenge concerns particularly receipts and cashier data that offer little information on the individuals who made the purchases. Receipts can be connected with individuals, if study participants have been recruited with study IDs, but cashier data can only provide data on unknown groups of people (e.g. Vanhatalo et al., 2022). Loyalty cards provide a feasible way of linking individual consumers with their purchases, since cardholders often are registered to retailer databases. However, loyalty-card data often fails to provide individual-level data on food choices, since cardholders typically use their loyalty cards to purchase foods also for their families and friends. Furthermore, since consumers often use more than one retailer and numerous catering services, food transaction data typically reveal only a part of consumers' overall food choices (Vuorinen et al., 2020).

Further challenges with food transaction data concern practicalities related to data collection and analysis, as well as privacy protection. Collecting receipts requires plenty of manual labour from the researchers, and the receipts may be in poor condition (Carroll & Samek, 2018). While loyalty-card and cashier data are less laborious to collect, getting access to these data might turn problematic, since retail chains may be unwilling to share their customer or sales data (Carroll & Samek, 2018). Even if access to the data is granted, the volume of data can be vast and may require substantial processing before meaningful analyses can be conducted. Challenges with privacy protection concern particularly loyalty-card data. As loyalty card systems often include personal information, researchers must receive informed consent from cardholders, and data handling and storing procedures must ensure the protection of cardholders' privacy. The need for informed consent may increase the risk of participant selection bias.

A challenge related to objective data collection through smartphone-based EMA tools is that they require self-reporting from the study participants. Even if participants record objective data, such as images of chosen foods or receipts of purchases, they still need to invest efforts in and remember to report required data—a challenge similar to subjective measures. A technical challenge with EMA tools is that they require users to have smartphones, which might lead to participant selection biases (Poelman et al., 2020).

3.3. Technologies for assessing eating actions and the type and amount of food consumed

The introduced sensor- and image-based solutions for objective and more automated eating-action and dietary-intake assessment (sections 2.3, 2.4, and 2.5) are largely in a prototype phase, where their feasibility has been tested in controlled or semi-controlled laboratory settings among small study samples and over short periods. In addition, methods are still under development for analysing and interpreting the data these solutions collect. Evaluations on the performance of image- and sensor-based methods have deemed that the accuracy of these methods holds promise, but falls still short of scientific standards and traditional self-reporting methods (e.g., Alshurafa et al., 2019; Bell et al., 2020; Eldridge et al., 2018; Ho et al., 2020; Höchsmann & Martin, 2020; Selamat & Ali, 2020; Skinner et al., 2020). Wider-scale use in the real world is challenged by the susceptibility of the methods to numerous disturbances and unsolved issues related to user comfort and privacy (e.g., Alshurafa et al., 2019; Bell et al., 2020; Doulah et al., 2019; Selamat & Ali, 2020; Skinner et al., 2020).

Regarding user comfort, a major challenge is to develop designs that both capture high-quality data and are comfortable to use (Selamat & Ali, 2020). Similar to psycho-physiological measurements for emotion detection (section 3.1) and eye-tracking glasses for studying visual attention and food choices (section 3.2), many sensor-based technologies developed for objective and automated eating-action or dietary-intake assessment require direct contact with skin and/or attachment to visible spots in the head or neck area (Farooq & Sazonov, 2018; Lopez-Meyer et al., 2012; Zhang & Amft, 2018). Such solutions may cause discomfort and tend to be sensitive to sensor placement (Farooq & Sazonov, 2018; Papapanagiotou et al., 2017; van den Boer et al., 2018). For example, firm attachment may require skin cleansing (Blechert et al., 2017) and medical tape (Sazonov & Fontana, 2012), and maintaining correct placement and orientation often require skills and effort (Bi et al., 2017; Chun et al., 2018). Furthermore, visible placement might raise concerns with social acceptability, and could consequently hinder user adoption (Farooq & Sazonov, 2018). Besides concerning sensor-based technologies, the issues related to correct placement and visible location apply to many image-based solutions as well (Alharbi et al., 2018; Chui et al., 2020; Doulah et al., 2021; Liu et al., 2012; Qiu et al., 2020; Sun et al., 2014).

Data protection is another important challenge that concerns both sensor- and image-based solutions, and that pertains to the privacy of both users and bystanders who could get inadvertently recorded (Alshurafa et al., 2019; Bell et al., 2020; Höchsmann & Martin, 2020; Selamat & Ali, 2020). Privacy issues concern particularly solutions that capture data automatically and/or continuously throughout the day, and that collect potentially identifiable and sensitive data, such as audio recordings or images. A user-study on wearable cameras found many participants to experience surveillance and/or social discomfort that could lead them to change their usual behaviour (Alharbi et al., 2018). The discomfort often stemmed from concerns about own or bystanders' privacy, as well as bystanders' observed or imagined perceptions of or reactions to the camera (Alharbi et al., 2018). Before wider-scale implementation, privacy issues around data collection, storing, and handling must be solved.

3.3.1. Challenges characteristic to sensor-based methods

Sensor-based approaches proposed for detecting eating actions (section 2.3) are prone to misinterpretations because of confounding signals that stem from activities unrelated to eating. This challenge is similar to the issues reported with emotion-detection technology (section 3.1), and concerns sensors detecting motion (Scisco et al., 2014; Sen et al., 2017), sound (Bi et al., 2018; Farooq et al., 2014; Liu et al., 2012; Mirtchouk et al., 2016; Thomaz, Zhang, et al., 2015), muscle contraction (Amft & Tröster, 2008; Blechert et al., 2017; Zhang & Amft, 2018), mechanical vibration and strain (Kalantarian et al., 2014; Sazonov & Fontana, 2012), and proximity (Bedri et al., 2015; Chun et al., 2018; Zhang, Zhao, et al., 2020). Some sensors are also sensitive to disturbances the user cannot control, such as the surrounding temperature (Sazonov & Fontana, 2012) or even hair touching the sensor (Zhang & Amft, 2016). While capturing irrelevant actions, sensors also miss relevant ones. Examples include transient eating moments such as eating a singleton candy (Sen et al., 2017) and actions performed with a non-monitored hand (Zhang & Amft, 2018). A focal source of the challenges with accurate eating detection is the diversity of eating styles, which depend on the individual, food type (e.g., soup vs. sandwich), eating posture (e.g., standing vs. sitting), and the mode of eating (e.g., eating with hands vs. fork and knife) (Sen et al., 2017; Thomaz, Essa, & Abowd, 2015; Zhang, Zhao, et al., 2020).

Sensor-based solutions proposed for food-type identification (section 2.4.2) are limited to classifying foods at a crude group level making the solutions incapable of uncovering the nutritional value of consumed foods. Solutions developed thus far have mainly employed sensors sensitive to sound (Amft & Tröster, 2009; Päßler et al., 2012), mechanical strain (Sazonov et al., 2009), or proximity (Chun et al., 2018; Zhang, Zhao, et al., 2020). These solutions rely on chewing detection, and are hence poor in identifying soft and liquid food consumption, which require little or no chewing (Amft & Tröster, 2008; Bi et al., 2018; Chun et al., 2018; Liu et al., 2012; Päßler et al., 2012; Sazonov et al., 2009; Zhang, Zhao, et al., 2020). Acoustic solutions classify foods based on chewing-sound characteristics that depend on food texture.

Challenges of these solutions include proneness to confound foods with similar textures, such as lettuce, carrot, and apple (Amft & Tröster, 2009), and difficulties in recognising composite foods with varying textures, such as sandwiches with toppings or noodles with sauce (Päßler et al., 2012).

Sensor-based approaches for estimating the amount of food consumed (section 2.5.2) rely on counting bites, chews, and/or swallows. Although bite count has been shown to correlate with energy intake (Scisco et al., 2014), and swallow count has been associated with the amount of food consumed (Kalantarian et al., 2014), building energy and nutrient intake assessment on the number of bites, chews, or swallows faces several problems. First, foods have varying energy and nutrient densities, but these densities are not directly associated with bite counts (Lorenzoni et al., 2019). Second, while chewing and swallowing patterns (Lopez-Meyer et al., 2012), as well as bite (Bellisle et al., 2000) and swallow (Sazonov et al., 2009) size have been shown to depend on food texture, texture does not reveal nutrient density. Since bites, chews, and swallows can merely identify foods at a crude group level, quantifying energy and nutrient intake based on these eating actions is possible only if detailed information on consumed foods is available from other sources, such as food composition or food product databases.

3.3.2. Challenges characteristic to image-based methods

While current image-based dietary assessment methods (sections 2.4.1 and 2.5.1) facilitate data collection and processing, reduce user burden (Höchsmann & Martin, 2020; Zhao et al., 2021), and potentially enhance user acceptance (Eldridge et al., 2018), researcher burden remains substantial (Höchsmann & Martin, 2020). Reviewing, analysing, and interpreting visual food intake data typically calls for trained nutrition professionals (Nyström et al., 2016; Pendergast et al., 2017; Rollo et al., 2015), and is time consuming and expensive (Skinner et al., 2020). In addition, these methods have not solved the key limitation of conventional self-reports: accurate dietary intake assessment. According to recent systematic reviews and meta-analyses, image-based dietary assessment underestimates energy intake similar to conventional self-reports (Ho et al., 2020), and human raters still produce more accurate estimates of dietary intake than semi-automated image analysis (Höchsmann & Martin, 2020).

Automating image-based dietary assessment requires advanced machine-learning methods capable of identifying and segmenting pixels in images that represent food, recognising the segmented food items, and estimating their volumes (Alshurafa et al., 2019). Finally, identified foods must be matched to food composition databases to obtain nutritional information (Alshurafa et al., 2019). While ongoing machine-learning research seeks to improve automated food recognition and volume estimation, fully automated solutions are not yet a reality (Höchsmann & Martin, 2020), and the accuracy of available methods falls short of scientific standards (Lo et al., 2020a; Zhao et al., 2021). Machine-learning methods show promise in classifying foods into food groups, but their ability to recognise individual food items remains limited (Skinner et al., 2020). These conclusions receive support from the findings of a study that compared the performance of seven freely available image-recognition platforms. Across a dataset of 185 food photos portraying altogether 32 various foods and beverages, the food-identification accuracy of the compared platforms ranged from 9% to 63%, and none of the platforms could estimate portion sizes (van Asbroeck & Matthys, 2020).

A key challenge in the development of automated food-image analysis is that training machine-learning methods requires large databases of food photos with ground-truth labels that clearly delineate and provide information on each food item in the image (Alshurafa et al., 2019; Jia et al., 2019; Skinner et al., 2020). Creating such databases is time consuming, and keeping the databases up to date is complicated due to the constantly changing food supply on the market (Alshurafa et al., 2019; Jia et al., 2019; Skinner et al., 2020). Furthermore, accurate identification of foods and their nutritional composition is not always possible based on food images, because images do not reveal food-preparation methods and hidden ingredients (Höchsmann & Martin, 2020; Zhao et al., 2021), such as fat, sugar, and salt. Due to this challenge and the difficulty of discriminating between similar-looking foods, food-image analysis may always require some degree of human input (Höchsmann & Martin, 2020; van Asbroeck & Matthys, 2020). Finally, the accuracy of image-based dietary assessment depends on image quality as well. Blurred images and images taken in poor lighting or from suboptimal angles or distances complicate image interpretation (Jia et al., 2019). Achieving sufficient image quality requires hence user training on correct ways of taking pictures (Nyström et al., 2016; Pendergast et al., 2017).

4. Recommendations for researchers and practitioners in nutrition, food-related consumer and marketing sciences to work around existing challenges

As portrayed in section 3, objective measurement technologies have numerous limitations—just as self-reports do. The key challenges can be summarised into four higher-level groups: 1) application in the real world, 2) obtaining accurate, reliable, and meaningful data with reasonable resources, 3) participant burden, and 4) privacy protection (Table 2). To facilitate a fruitful use of the reviewed technologies, we discuss ways to work around identified challenges.

4.1. Applicability in the real world

To obtain study outcomes with higher predictive validity, an ideal would be to bring technologies from laboratories to more realistic settings. The first step in this transition is to create experimental set-ups that resemble real-wold settings as closely as possible. This could be achieved with, for example, virtual reality headsets (Melendrez-Ruiz et al., 2022; Siegrist et al., 2019) or naturalistic laboratories that provide real food and that simulate real food-choice and eating environments (e.g., Puurtinen et al., 2021). The next step is to bring study participants to real food environments, such as supermarkets or restaurants, yet control participants' food choice and eating tasks (e.g., Bialkova et al., 2020; Fenko et al., 2018; Wang et al., 2018). Ultimately, when the technologies are flexible and mature enough, studies can monitor food choices and eating in fully unconstrained real-world settings. We recommend collaboration with technology experts that have up-to-date knowledge on the capabilities and limitations of desired technologies and that can assist in choosing and/or designing technological solutions that best fit each study set-up and that produce data that is able to answer defined research questions. Since novel and/or expensive technologies often allow only small study samples and short data collection periods, research groups could join forces to enable the collection of larger datasets (Puurtinen et al., 2021).

4.2. Obtaining accurate, reliable, and meaningful data

One way or another, all reviewed technologies face the challenge of producing accurate, reliable, and meaningful data with reasonable resources. These challenges have to do with the capabilities of the measurement technologies per se and the processes developed to analyse technology-driven data.

With sensor-based technologies, a focal challenge is their susceptibility to external conditions such as outdoor temperature and confounding signals, such as non-targeted sounds and activities. To overcome this challenge, one opportunity is to compose sensor modules of multiple sensors that complement one another and compensate one another's weaknesses (Blechert et al., 2017), and that allow the removal of confounding signals (Fontana et al., 2014). In sensor-based eating detection, for example, complementing acoustic, vibration, or proximity sensors with motion sensors enabled the removal of motion artefacts

Table 2
Key challenges of reviewed technologies, study domains that each challenge concerns (x), and recommendations for nutrition research, food-related consumer and marketing research.

Higher level challenge	Lower level challenge	Study domain					Recommendations for researchers and practitioners
		Emotions	Food choice	Eating actions	Food type	Food amount	
Application in the real world	Application is largely restricted to laboratory or simulated real-world settings, small study samples, and short periods.	x		x	x	x	– Collaborate with technology experts and familiarise yourself with the desired technologies to learn about their capabilities and application-related constraints. – If the technology cannot be brought to real-world settings, try to create experimental conditions that resemble real-wold settings.
Obtaining accurate, reliable, and meaningful data with reasonable resources	External conditions and confounding signals compromise the performance and accuracy of sensor-based devices.			x	x	x	– Employ multiple sensors that complement one another. – Accompany automated sensor-based solutions with functionalities that allow users to confirm or correct sensor-detected data.
	The data that technologies capture are limited and often difficult to interpret.	x	x	x	x	x	– Complement data collection with self-reports, for example, by allowing users of mobile/wearable devices to submit images, voice recordings, text annotations, location data, and/or answers to real-time questionnaires. – Integrate food data with food composition and/or food product databases to retrieve nutritional information on consumed foods.
	Data analysis remains resource intensive.	x	x	x	x	x	– Ensure needed resources and expertise for handling collected data. – Employ undergraduate research assistants in less-demanding tasks.
	Automated data processing and analysis require further development to meet scientific standards and to outperform manual analysis.			x	x	x	– Collaborate with computer scientists to learn about the capabilities and limitations of available automated analysis methods. – Prepare to confirm and complement automated processes with manual procedures.
Participant burden	Obtaining high quality data requires substantial user effort and training.			x	x	x	– Ensure that participants receive sufficient training and support for using wearable/mobile devices. – Provide participants feedback to motivate sustained use of wearable/mobile devices and to improve the quality of recorded data. – Accompany wearable/mobile devices with prompts that remind participants to use the devices and to record desired data.
	Wearable solutions compromise user comfort.	x	x	x	x	x	– Favour wearable devices that do not require attachment to skin. – Favour wearable devices with unnoticeable placement on the body. – Invest in reducing the size of wearable devices. – Invest in improving the look of wearable devices.
Privacy protection	Privacy protection of users and bystanders.	x	x	x	x	x	– Favour solutions that do not collect identifiable data on users or bystanders. – Limit the scope and continuity of data collection. – Allow users to control the onset and offset of data collection, and to review and remove recorded data.

(Bedri et al., 2015; Bi et al., 2018; Kalantarian et al., 2015; Mirtchouk et al., 2017). Another opportunity is to accompany sensor solutions with functionalities that allow users to approve or correct sensor-detected events, such as the onset and end of meals (Dong et al., 2014).

While technologies can substantially facilitate data collection, collected data may remain incomplete and incapable of answering research questions comprehensively. Food images, for example, do not reveal hidden ingredients nor the nutrient composition of portrayed foods. Image-based dietary assessment requires hence additional information from complementary data sources, such as participant self-reports and food composition or food product databases. The same applies to sensor-based dietary assessment. Feasible platforms for complementary data collection include smartphone applications that enable the real-time collection of diverse data on food choices, eating contexts, meal rhythm, and/or dietary intake. Means for data collection are numerous, including GPS, photos, text descriptions, and voice recordings (e.g., Nyström et al., 2016; Pendergast et al., 2017; Poelman et al., 2020; Rollo et al., 2015; Widener et al., 2018).

Besides remaining incomplete, technology-driven data may also be difficult to interpret without complementary data sources. Food-related emotion detection, for example, has benefitted from self-reports such as subjective food evaluations that have complemented and supported the interpretation of motion tracking and/or psycho-physiological measurements (de Wijk & Noldus, 2021; Pennanen et al., 2020). Potentially beneficial measurement combinations for food-related emotion research include valence-dominant questionnaires such as the EsSense Profile™ and objective measures of arousal, including heart rate, skin temperature, and skin conductance (Cardello & Jaeger, 2021).

Despite advances in technology-assisted data collection, handling technology-driven data often remains resource intensive, requiring trained professionals and substantial manual work. In addition, with technology-assisted dietary intake assessment, automated data analysis requires further development to meet scientific standards. Researchers must hence prepare to complement and confirm automated data handling processes with manual procedures, and ensure needed resources and expertise for such tasks. Again, we recommend collaboration with computer scientists to learn about the capabilities and limitations of available automated analysis methods, and to design most feasible ways to confirm the accuracy of technology-driven data. One way to cope with limited resources is to employ undergraduate research assistants to support data handling procedures that require less experience and expertise. With food transaction data, for example, such procedures could mean the labour-intensive task of manually organising and entering data from receipts to desired software (Carroll & Samek, 2018). Sensor- and image-based solutions for automated dietary assessment, in turn, could benefit from the above-mentioned features that allow participants to confirm or correct technology-inferred data real time (e.g., van Asbroeck & Matthys, 2020).

4.3. Participant burden

Participant burden refers to the efforts participants must put into data collection, and the perceived discomfort that wearable technologies may cause. With mobile and/or wearable devices that participants use in experimental settings or independently in the real world, obtaining high-quality data often requires skills and effort from study participants. Participants should hence receive sufficient training and support for using the devices and for recording desired data. In virtual reality (VR)-assisted eye-tracking experiments, for example, unobstructed participation proved possible when participants could familiarise themselves with the VR environment before experimental tasks (Siegrist et al., 2019). With wearable and mobile devices that participants use independently over longer periods in real-word settings, encouraging feedback on device use and on the quality of recorded data could motivate further use and enhance reporting. To avoid memory bias and to reduce cognitive load, these devices could provide reminders that prompt participants to use the devices and to record desired data. A smartphone application for food-choice monitoring, for example, sent pre-programmed text messages that reminded users to report purchased foods and any challenges encountered with the app use (Poelman et al., 2020). Alternatively, such reminders could be triggered by GPS-derived location data that indicates visits to food choice and eating environments. In mobile applications for dietary intake assessment, an additional opportunity is to accompany the applications with sensors that automatically detect the onset of eating and consequently prompt users to record their meals (Blechert et al., 2017).

To improve user comfort, when feasible, we recommend employing wearable devices that do not require attachment to skin and that can be placed on unnoticeable spots on the body. Additionally, we encourage efforts to reduce the size and to improve the look and feel of wearable devices. An example of such efforts was a wearable multi-sensor solution designed for long-term monitoring of food-evoked emotions. This solution embedded heart rate, respiration, and skin conductance sensors in bras that were washable and available in varying sizes (Carroll et al., 2013).

4.4. Privacy protection

Regarding user and bystander privacy, an ideal would be to stick to solutions that do not collect identifiable data on users or bystanders, for example, depth cameras that recognise shapes but not individuals. Avoiding the collection of identifiable or otherwise sensitive data is not always possible, however. In such situations, privacy can be promoted by limiting the scope and continuity of data collection, and by allowing users more control over recording devices and recorded data. With wearable cameras, for example, privacy-promoting opportunities include technical approaches, such as lower resolution and blurring of faces, as well as camera recording affordances, such as adjustable camera location and lens orientation (Alharbi et al., 2018). These measures facilitate minimising recorded details, limiting the recording to objects of interest, and mitigating surveillance and social discomfort that users and bystanders may experience (Alharbi et al., 2018).

5. Conclusions

Nutrition research, food-related consumer and marketing research build on self-reports that depend on individuals' introspection and memory, and that hence suffer from limited reliability, validity, and applicability. Numerous objective measurement technologies have been developed to solve the problems inherent in self-reports. We reviewed the capabilities and challenges of technologies applied in five food- and nutrition-related study domains: food-related emotions, food choices, eating actions, and the type and amount of food consumed. Additionally, we touched upon potential technologies not yet applied in the targeted domains. Key challenges of reviewed technologies concern application in the real world; obtaining accurate, reliable, and meaningful data with reasonable resources; burden on study participants, and privacy protection. We provided recommendations for researchers and practitioners in nutrition, consumer, and marketing sciences to work around the key challenges. For fruitful application of available technologies, we additionally encourage collaboration between technology developers and experts in the fields of nutrition, food-related consumer and marketing research.

Funding

This work was supported by Business Finland as part of the Me and My Food co-creation project (43,029/31/2020), and by the Food Economy 4.0 program of VTT Technical Research Centre of Finland Ltd. The sponsors were not involved in designing the study; in collecting, analysing, or interpreting data; in writing the manuscript; or in the decision to submit the manuscript for publication.

CRediT authorship contribution statement

Eeva Rantala: Conceptualization, Methodology, Formal analysis, Visualization, Writing – original draft. **Angelos Balatsas-Lekkas:** Conceptualization, Methodology, Formal analysis, Writing – original draft. **Nesli Sozer:** Writing – review & editing, Funding acquisition. **Kyösti Pennanen:** Conceptualization, Methodology, Writing – review & editing, Project administration, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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