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SPECIAL ARTICLE

Dietary Intake and Physical Activity Assessment: Current Tools, Techniques, and Technologies for Use in Adult Populations

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Accurate assessment of dietary intake and physical activity is a vital component for quality research in public health, nutrition, and exercise science. However, accurate and consistent methodology for the assessment of these components remains a major challenge. Classic methods use self-report to capture dietary intake and physical activity in healthy adult populations. However, these tools, such as questionnaires or food and activity records and recalls, have been shown to underestimate energy intake and expenditure as compared with direct measures like doubly labeled water. This paper summarizes recent technological advancements, such as remote sensing devices, digital photography, and multisensor devices, which have the potential to improve the assessment of dietary intake and physical activity in free-living adults. This review will provide researchers with emerging evidence in support of these technologies, as well as a quick reference for selecting the "right-sized" assessment method based on study design, target population, outcome variables of interest, and economic and time considerations.

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INTRODUCTION

Accurate assessment of dietary intake (DI) and physical activity (PA) is essential for quality research in the fields of public health, nutrition, and exercise science. However, consistent and accurate estimation of both remains one of the largest challenges in these fields. Several subjective and objective measures of DI and PA assessment exist, each with its own limitations and biases.

Capture of DI in healthy adult populations is intricate and multidimensional, thus making accurate quantification challenging. DI is traditionally assessed using self-report measures, including food frequency questionnaires (FFQs), diet records, and recalls.[1–3] Such self-report measures have been shown to underestimate energy intake by approximately 11%–35% (more prevalent among obese individuals) compared with direct measures like doubly labeled water.[4–7] Reporting error that includes bias, also known as systematic error, misestimation, and

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random error, and error related to nutrient databases for foods being reported are a few of the current criticisms that have questioned the adequacy of self-report DI measures as the basis for scientific conclusions regarding the link between DI and health.[8–11] From the findings in studies with doubly labeled water, researchers have suggested that self-report measures should not be used to estimate energy intakes, but that they are useful to estimate usual intakes of other nutrients and food groups and their densities, inform nutrition policy, and assess diet and disease associations.[12] Several recent reports suggest that investigators should work to improve and apply newer methods of DI assessment suitable for use in free-living individuals, such as biomarkers,[4,13,14] remote sensing devices,[15,16] or digital photography,[17] rather than continue to rely solely on self-report methods.

PA is typically assessed using both self-report measures and devices. Self-report measures of PA include administration of questionnaires and completion of detailed diaries or logs. Device-based measures include motion sensors, such as accelerometers, pedometers, heart rate (HR) monitors, and multisensor devices.[18] Because of the complex and multidimensional nature of PA, precise quantification can be difficult.[19] Improvement and innovation are needed to provide low-cost, accurate measures of PA for use in both large and small samples of free-living healthy adults.

The use of technology for individualized DI and PA assessment has expanded rapidly over the past decade.[20–24] Although technology has brought about some advances in diet and PA assessment methodology, many limitations and challenges remain. The purpose of this paper is to review the current science and challenges in the assessment of DI and PA for healthy adults and to identify current gaps and future needs.

DIETARY INTAKE ASSESSMENT

Methods of DI have been assessed using several objective and subjective tools, each with its inherent strengths and limitations. Selection of the right tool for use in research varies, depending on the study design, nutrients of interest, target population, and economic and time resources available. Some caution the adequacy of self-report DI measures as the basis for scientific conclusions regarding the link between DI and health outcomes.[8–10] However, traditional DI assessment measures (FFQs, diet records, and recalls) remain the mainstay in the field based on their cost and familiarity, as well as lack of consensus among more objective methods capable of providing the complex output required. Although these measures may be criticized for not being precise, such data remain useful for population guidance in maintaining healthy eating practices, comparison across populations, informing nutrition policy, and elucidating the associations between diet and disease.[12] Additional information on traditional DI methods and the controversy can be found in recent reviews by Farshchi et al.,[25] Dhurandhar and colleagues,[9] Archer et al.,[10] Shim and colleagues,[26] and Kirkpatrick et al.[27] Additionally, researchers are encouraged to utilize the Dietary Assessment Primer by National Cancer Institute (NCI) to help them determine the best way to assess diet for any study in which estimates of group intakes are required.[28]

Current Dietary Intake Technology

Recent advances in technology have led to the development of several automated dietary assessment tools that have overcome some limitations of the traditional subjective tools, while striving to meet time and cost efficiency. Although modern DI methods are attractive, researchers should consider that these methods often do not differ in errors associated with underreporting and reactivity as compared with traditional methods. Current examples of modern methods include automated 24-hour recalls and food records,[29,30] automated and graphic FFQs, photo-assisted dietary assessments (PADAs),[31–38] and image-based dietary assessments (IBDAs).[39–45] Table 1 summarizes the current and emerging DI assessment tools using technology.

The NCI introduced a modified version of the U.S. Department of Agriculture's Multiple-Pass 24-Hour Recall Method enabling 24-hour recalls to be self-administered by a respondent (ASA24) and used over multiple days as a food record.[46] Multiple versions (i.e., languages) have since been released and are detailed elsewhere.[47] The ASA24 improves on the limitations of traditional 24-hour recalls, including lack of reliance on trained interviewers, reduced time and economic burden to the researcher, and reduced respondent burden.[48] Because of the need for a high-speed Internet connection and familiarity with Internet or web-based tools, the use of the ASA24 may be limited in some populations.

In an effort to limit the issues with paper-based traditional FFQs,[49] a number of innovative web-based self-administered FFQs have been developed to automate the tool, such as the NCI Block questionnaire developed by Nutrition Quest,[50] NCI's Diet History Questionnaire (DHQ) III,[51] and the Fred Hutchinson Cancer Research Center FFQ.[52] All are web based and contain 100 or more questions on food items, purchasing, and preparation, with variations in layout design and analysis (e.g., food lists and databases) with NCI's DHQ III free for use by researchers. A novel alternative, VioScreen, offers a graphical FFQ option that addresses limitations of traditional FFQs by utilizing

Table 1. Summary of Current DI Assessment Tools Using Technology

Method/ tool	Outcome measure	Appropriate population	Attributes	Limitations	Validity	Research gaps	References
PADA	Researcher-defined nutrient output, such as energy intake, nutrient intake, food groups, and individual foods	Individuals and small groups	DLW validation; includes objective measure plus self-report	Participant burden to collect photos; researcher burden for post-analysis; self-report measure may not suitable for low-literacy populations	Estimate of energy intake −8.8% to 6.8% error compared to DLW	Automated post-analysis to include large food database	31–38
IBDA	Energy intake and volume estimates	Individuals and small groups; laboratory data collection	Low participant burden; no self-report	Data storage; high error rates or not validated to estimate energy/nutrient intake; ethical issues	Underestimated energy intake by ∼23% compared to DLW; mean portion size difference compared to seed displacement is −5% ± 21.1%	Automatic analysis of data can estimate volume and requires food density to convert to nutrient intake; most food-nutrient databases lack density values	39–45
Automated 24-hour recall/ food record	Short-term DI, including energy intake, nutrient intake, food group, and individual foods; provides indicators of overall diet quality	Individuals, small groups, and large groups	Self-administered; eliminates the need for an interviewer and coding of intakes; captures short-term diet; accessible by individuals using assistive technologies, such as screen readers; uses images to assist respondents in reporting portion size	Restricted to populations with access to computers, high-speed Internet, and familiarity with web-based tools; not suitable for low-literacy populations	Underreporting of energy intake ∼11% to 35% compared to DLW; 72% of items consumed were exact or close matches to reported; use to obtain food record data has not been evaluated	Accurately reports energy intake in normal-weight subjects; however, research is warranted to enhance its accuracy in overweight and obese individuals	8, 46–48
Automated FFQ	Frequency and portion size of foods and beverages consume over a long-term period; can also be used to assess usual DI or particular aspects of diet, including food groups and individual foods	Individuals, small groups, and large groups	Self-administered; low cost; low researcher burden; captures long-term diet (months); not affected by reactivity	Not suitable for low-literacy populations; restricted to populations with access to computers; limited application among ethnic populations due to its finite list of foods and beverages; poor measure of energy intake and some micronutrients with variable preparations; not useful for estimating a population's intake	Underestimated energy intake by 24% to 33% compared to DLW	Diverse food list/nutrient data for more universal use	49–52

(*continued on next page*)

Table 1. Summary of Current DI Assessment Tools Using Technology (*continued*)

Method/ tool	Outcome measure	Appropriate population	Attributes	Limitations	Validity	Research gaps	References
Graphic FFQ	Frequency and portion size of foods and beverages consumed over a long-term period; can also be used to assess usual DI or particular aspects of diet including food groups and individual foods	Individuals, small groups, and large groups	Improved DI and dietary pattern assessment through the use of improved portion size estimation via food images; self-administered; low cost; low researcher burden; uses branching logic to reduce completion time; captures long-term diet (months); not affected by reactivity	Not suitable for low-literacy populations; restricted to populations with access to computers; limited application among ethnic populations due to its finite list of foods and beverages; poor measure of energy intake and some micronutrients with variable preparations; not useful for estimating a population's intake	Compared to traditional FFQs, nutrient correlations are 0.90 for alcohol, 0.84 for saturated fat, 0.82 for fat, 0.79 for carbohydrate, and 0.67 for protein	Diverse food list/nutrient data for more universal use	53,54
Smart kitchen (e.g., plates, tables)	Researcher-defined nutrient output; frequency and portion size of foods and beverages consumed over a long-term period	Individuals and small groups; laboratory or home-based data collection	Reduced participant burden; streamlined researcher collection and analysis	Limited eating environments; strength of nutrient data is dependent on database used for coding	Validity based on quality of inputs, including weights, images, and sensor-based data; nutrient database selection	Use in real time; development of enhanced computer vison systems; validation studies	55,56
UPC or grocery store purchase data	Nutrients limited to food label; foods and beverages purchased over a long-term period	Large populations, as an adjunct to mobile apps	Ease of collection, time efficient, and minimal training of participants	Data are of food purchases and not consumed intake (DI assumed); large amount of data; individualized DI difficult to interpret; nutrients limited to food label (some missing nutrient data); privacy concerns	Association of foods purchased to food group mapping: 77%–100%; agreement between UPC scanned data home food inventory: ~95%	Real-time data use and feedback; accountability for waste; validation studies; database use transparency	57,58
Body-worn monitors	Time and duration of food intake; meal microstructure; estimates of mass and energy; food imagery	Individuals and small groups	Potential ease of data collection; no self-report in some methods; potential use in just-in-time interventions	Not well tested (yet); sensors may not detect certain foods; the nutritional value of ingested foods is not measured directly; stigma to wearing the device; personal privacy of bystanders	Up to 90.1% accurate at identifying when a person is consuming food	Large-scale validation across populations and environments	59–67

DI, dietary intake; DLW, doubly labeled water; FFQ, food frequency questionnaire; IBDA, image-based dietary assessment; PADA, photo-assisted dietary assessment; UPC, Universal Product Code.

branching questions (i.e., avoids lost data and limits respondent burden) and offers multiple photographs for each food item to accurately capture serving size (i.e., avoids need for respondents to calculate DI into a standard serving size).[53,54]

PADAs, in which images of food selections and any food remaining after the meal are used to estimate DI, may provide an efficient, unobtrusive method for DI assessment in large groups of free-living individuals. PADAs have been utilized to assess DI in military recruits during basic training,[31,32] young adults,[33,34] individuals with disabilities,[35,36] and overweight and obese women.[37] PADA methods include traditional methods (photo match to weighed food standard),[38] as well as technological advancements with remote food photography[37] and digital photography plus recall,[34] both validated to direct energy measures (e.g., doubly labeled water) under different environmental and population extremes. PADA is limited by a lack of full automation for nutrient analysis after photo capture and the quality of the nutrient database used in analysis.

IBDAs are a technique in which images of food selections and any food remaining after the meal are used to estimate DI. Unlike PADA, IBDA image capture is passive (e.g., automatic from the device) and relies on the captured images as the main source of information with input from the user only for verification.[39] Updated versions of IBDAs have combined with automated food identification and portion size estimation software, as well as user prompts, in an attempt to accurately assess DI. Examples include the Nutricam Dietary Assessment Method,[40] the eButton,[41] and the Technology-Assisted Dietary Assessment system.[42–44] Most advanced is the mobile food intake visual and voice recognizer,[45] which incorporates mobile phone food photography methods using image recognition with speech recognition and physical location (mobile phone accesses to a GPS). Although IBDA minimizes participant and researcher burden during data collection, the amount of data influx is vast and requires further work to streamline data cleaning and analysis for efficient researcher/user feedback.

Emerging Dietary Intake Technology

One of the largest areas of technological growth is in sensors for DI assessment.[55] A majority of technologies are geared toward the consumer and have inherent flaws (per the research community), whereas others are in their infancy and show potential with future improvements and testing.

In an effort to improve data accuracy and participant burden, some techniques and tools aim to identify foods and portions consumed through the automation at the point of sale or food preparation (e.g., the kitchen). Ease of capturing Universal Product Codes[57] and Global Trade Item Numbers with handheld scanners or smartphones enables the correct item type to be properly linked with serving size and nutrition information at the time of consumption.[58] Alternatively, use of grocery store receipts (e.g., data capture) is an attractive option to minimize participant burden with direct feed into a food record for timely DI assessment (e.g., eliminate matching food type and brand consumed with specific database item). Traditional portion size estimation methods use standardization tools, cards, or even anatomical measures (e.g., the user's thumb) as a reference for improved accuracy of written DI assessments or PADAs.[55] Preliminary studies have looked at the use of smart kitchen equipment (e.g., plates, bowls, and tables) capable of recording food weight (with or without plates) before and after meal consumption.[56]

Wearable sensors offer automated capture of food consumptions through hand-to-mouth gestures,[59,60] modality of chewing (e.g., microphones to detect food crushing,[61] electromyographic sensors to detect muscle activations,[62] or strain and acceleration sensors to capture the chewing motion[63]), or swallowing frequency.[64–66] Chewing monitors have been shown to be reliable indicators of ingestion in community-dwelling individuals.[16] Of interest, chew counts show good correlation to ingested food mass.[67] However, they may be prone to false detections (e.g., because of gum chewing) and may not detect all liquids, although consumption of certain liquids (e.g., sucking through a straw) creates jaw motion similar to chewing and thus may potentially be detected. Swallowing has been shown to be one of the most reliable indicators of DI, as any food requires swallowing to contribute to nutrition. Consumption of both solid and liquid foods manifests as an increase in swallowing frequency[64] over spontaneous non-nutritive swallowing. Swallowing sensors include microphones,[65] electrical sensors, or motion sensors.[66] The frequency of swallowing may be used to differentiate consumption of solids and liquids,[64] and the count of swallows per meal may serve as an indicator of the amount consumed.[67] In general, a significant strength of the sensor-based approaches is that in most (not all) of these, the food intake can be detected automatically, without self-report. However, the technology behind sensor devices is new and most have not been thoroughly tested and validated for use in community-dwelling individuals, and there is concern that wearing the device may cause some reactivity bias. Furthermore, sensor devices can only detect the total amount of food ingested and are unable to identify types of foods, portion sizes, nutrient composition, or energy intake.[55,68]

Other sensor- and informatics-based research tools have been developed to determine food type and nutritional composition, for example, food classification-based acoustical sensing,[61] use of miniaturized hand-held (near-infrared) spectrometers that can scan food items and determine characteristic food matrix properties,[69] or recent miniaturized tooth-mounted sensors capable of detecting nutrients and wirelessly communicating to a mobile device.[70] Such technologies are still under research and development at this time, and many require support of comprehensive nutrient databases to support the technology and methodology to assess portion size.

PHYSICAL ACTIVITY ASSESSMENT

Similarly to DI, the assessment of PA can be measured through self-report or device-based techniques.[18,19] Researcher-selected PA methods and tools are influenced by cost, participant burden, sample size, collection time frame, type of information required (e.g., steps, counts, energy expenditure [EE]), data management, and measurement error.[71,72] The following section provides a brief overview of PA assessment tools. Additional information can be found in recent reviews by Ainsworth and colleagues,[18] Sylvia et al.,[73] Welk and colleagues,[74] and the Physical Activity Resource Center for Public Health (www.parcph.org/). PA assessment techniques are summarized in Table 2.

Device-Based Physical Activity Assessment Tools

Research grade devices. Triaxial accelerometers, such as the ActiGraph wGT3X-BT, measure PA volume and intensity. They are commonly worn on the wrist or hip, with the hip location providing better accuracy.[80–83] The major strength of accelerometers is their ability to collect large amounts of data and measure intensity level. Limitations include expense and the inability to provide contextual information. Furthermore, data collection protocols (e.g., hip versus wrist placement, waking-hour versus 24-hour registration period) and data analysis approaches (e.g., non–wear-time definition, cutpoints for intensity classification) vary, making it very difficult to compare across studies.[84] Researchers have traditionally used "activity counts" to classify PA as light, moderate, or vigorous intensity, but the field is shifting to activity characterization from raw acceleration signals.[85,86] Lastly, researchers are working to improve the ability to analyze data from wrist-worn devices,[83,87,88] which may improve compliance.[85] For an extensive discussion of considerations when using accelerometers, see the 2017 review by Migueles et al.[84]

The activPAL is a particularly useful device for researchers interested in sedentary behavior.[108,109] The activPAL is affixed to the thigh, which makes it uniquely capable of assessing postures (e.g., sitting versus standing). The device also measures step cadence and number of steps, therefore allowing activity to be classified as sitting, standing, or stepping. There is promising evidence that the activPAL can also accurately classify PA intensities.[110,111] For an extensive discussion of considerations when using the activPAL, see the review by Edwardson and colleagues.[89]

HR monitors are used in laboratory settings to assess exercise activity, intensity of the activity, and EE of activity[90,91] due to the direct and linear relationship between HR and oxygen consumption.[92] Recently, HR monitoring has been combined with accelerometry to more accurately account for the predictive power of HR at rest and during light activity in EE estimates.[93]

GPS units enable collection of altitude, longitude, latitude, speed, distance traveled, and elevation data.[94,95] Commercial GPS units can be accurate up to 15–20 meters; however, the clarity of the device signal to the satellites is crucial, affecting sample rates and signal validity.[96,97] Compared with accelerometers, GPS units significantly underestimate PA (i.e., EE).[98] There have been suggestions to use GPS in combination with HR monitors and accelerometry.[97,99]

Multisensor devices utilize multiple physiological and mechanical sensors in combination to improve precision of PA and EE measurements. For example, the SenseWear armband is worn on the upper arm and incorporates triaxial accelerometry, heat flux, galvanic skin response, skin temperature, and near-body ambient temperature to accurately determine when the device is being worn (i.e., a major consideration with traditional accelerometers).[100] These measures, in combination with entered data, enable accurate estimation of EE, minutes of activity, and sleep.[101–105] However, Jawbone Inc. acquired BodyMedia in 2013 and discontinued support of the SenseWear armband. Thus, this device is no longer available for purchase. Another device, the Intelligent Device for Energy Expenditure and Activity, incorporates five sensors (chest, right and left thighs, and right and left legs) connected to a digital recorder that allows identification of 32 different activities and body postures for estimation of PA level and accurate EE.[106,107]

General-Use Devices

Pedometers are simple devices that measure steps. They are inexpensive and useful in assessing behavioral feedback and motivation.[118] Pedometer accuracy has improved with transition into microelectromechanical-based systems[112] specifically with measurements more than 2 mph.[112–115] Pedometer output can vary

Table 2. Summary of Device-Based PA Assessment Tools

Method/tool	Appropriate populations	Outcome measure	Attributes	Limitations	Validity	Research gaps	References
General-use wearables (Fitbit, Garmin, Apple)	Large population; behavior change within individuals	EE	Popular; ease of collection and data upload (wireless); large amounts of data collected	Not a valid measure of TEE; underestimates free-living EE; overestimates PAEE; algorithms change with updates; not designed for research; cost to obtain data	Correlation between consumer activity monitors and accelerometers for sleep count and step count, $r > 0.8$; for TDEE, $r = 0.74$ to 0.81; and MVPA, $r = 0.52$ to 0.91	More accuracy research is needed	75–79
Accelerometers	Large populations	Minutes of physical activity, intensity	Commonly used in research settings and by NHANES; ability to collect large amounts of data	Expense; inability to provide contextual information; data collection protocols (e.g., hip vs wrist placement, waking-hour vs 24-hour registration period) and data analysis approaches (e.g., non-wear-time definition, valid day criteria, cutpoints for intensity classification) vary, making it very difficult to compare across studies using accelerometry	Correlations between daily PAEE and activity counts for the hip-worn ActiGraph range from $r = 0.77$ to 0.90; compared to wearable cameras measuring PA, hip-worn accelerometers had 89.4% accuracy and wrist-worn accelerometers had 84.6% accuracy	Lack of consensus regarding data processing	80–88
GPS	Large populations; outdoors	Distance and speed	Ideal use outdoors (free-living walking and running) or field testing	Underestimates EE for field activities; not a standalone measure for EE; not appropriate for indoor activities; issues with battery life	Compared to accelerometers, GPS underestimates EE by 42% to 50%	Stronger association with EE measure (accelerometer use)	89–95
HR monitor	Supervised exercise	HR, activity intensity	Direct measure, high validity to clinical measures	Uncomfortable when worn for long periods of time; not a valid estimate of EE at rest; must have an HR-O_2 consumption curve for each person to measure their intensity; TDEE is hard to predict because daily HR is not linear	During PA, EE error rates are <3% compared to whole-room calorimetry; however, when doing light or sedentary activity, they have poor predictive power in terms of EE	Improved estimates of TEE	96–99

(*continued on next page*)

Table 2. Summary of Device-Based PA Assessment Tools (*continued*)

Method/tool	Appropriate populations	Outcome measure	Attributes	Limitations	Validity	Research gaps	References
Multisensor	Populations with a wide range of activities	Minutes of PA, EE	Multiple mechanical and physiological sensors improve estimates	Cost, availability	SenseWear: EE and activity ICC of 0.81–0.85 compared to DLW; IDEEA: EE within 98.9%±9.0% compared to indirect calorimetry	Improved estimates of individual-level estimates	100–107
ActivPAL	Large populations	Sedentary time, steps/day	Can be worn 24 hours/day	Relatively small body of literature compared to other accelerometers	Correlations range from 0.78 to 0.99 against direct observation	Validation for EE	88, 108–111
Pedometers	Large populations	Steps/day	Affordable; best used to assess walking; steps/day is well understood by the lay population; newer versions store data	Inaccurate at slow speeds; inter-individual variability-based difference; in some models, must manually record steps; readings vary according to anatomical location (e.g., hip or ankle)	Varies by model	Estimations of EE and exercise intensity	71–74, 80, 112–117

DLW, doubly labeled water; EE, energy expenditure; HR, heart rate; ICC, intraclass correlation coefficient; IDEEA, Intelligent Device for Energy Expenditure and Activity; MVPA, moderate to vigorous physical activity; NHANES, National Health and Nutrition Examination Survey; PA, physical activity; PAEE, physical activity energy expenditure; TDEE, total daily energy expenditure; TEE, total energy expenditure.

according to location worn (e.g., the ankle is the most accurate placement)[114,116] or among individuals (e.g., foot-strike variability).[117]

Recently, commercial off the shelf (COTS) activity trackers from Fitbit, Garmin, and Apple have exploded onto the consumer market.[75] These newer devices use advanced technologies allowing expansion of monitoring capabilities (e.g., accelerations, HR, EE, and sleep) and are able to transmit and store PA data to smartphones, computers, and cloud-based storage. New devices and algorithm updates are released frequently with expanded capability to detect posture changes and type of activity for more accurate and precise estimates of EE. These wearables provide health data that are instantly available to the consumer through a smartphone application. Such wearable devices employ multiple engagement strategies to make them more attractive and interactive for the individual.[76]

Popularity in the marketplace has led to more research in the past 3–5 years to validate accuracy and reliability of EE for COTS wearables compared with more traditional measures, such as the ActiGraph.[76–78,111] Compared with EE measured by doubly labeled water, COTS wearables underestimated EE in free-living, normal-weight men and women aged 21–50 years.[79]

Other limitations to using COTS wearables for EE assessment in research include the lack of transparency of cutpoint data and algorithms used to calculate activity intensity and EE. Data management can also become overwhelmingly expensive, and many companies employ a third party to clean and organize the data. COTS wearables were not developed to be research grade; therefore, inclusion of third-party sites for data management makes it difficult for researchers to obtain required data necessary for analysis.

CONCLUSIONS

Accurate measurement of DI and PA is needed for both population- and intervention-based assessments. Although there are many limitations to the measurement of DI and PA, there is progress and promise for using technology to improve these measures. Managing the current knowledge base and facilitating a resource center for new technology integration are key to the future success of accurate DI and PA measures through device-assisted methods.

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HLM, LTP, AA, ES, RW, and SKD composed and drafted the dietary intake information and table. RPS, AMG, and KB prepared and drafted the physical activity information and table. HLM, LTP, and SKD edited the manuscript. All authors read and approved the final manuscript.

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