Innovative Dietary Assessment Technologies to fill the (Micro-) Nutrient Data Gap

Sara Jansen

Micronutrient data is needed to understand combined forms of malnutrition and their health consequences. This is rather important e.g. for geriatric nursing and clinical nutrition. This report presents current efforts to close the gap in individual (micro-)nutrient data, focusing on low income countries. Three methods using innovative technologies for optimizing dietary assessment are presented: the INDDEX24 app, the Automated Ingestion Monitor (AIM) and handheld spectrometers. While for INDDEX24 implementation is underway and for AIM free living validation is planned, for the handheld spectrometers a lot of work still needs to be done to make them an accurate method for broad nutrient analysis.

Keywords: nutrition assessment, low-income countries, NIR-spectroscopy, minerals, machine learning

Innovative Technologien der Ernährungserhebung zur Schließung der (Mikro-) Nährstoffdatenlücke

Mikronährstoffdaten sind notwendig, um die verschiedenen Formen von Mangelernährung und ihre gesundheitlichen Folgen zu verstehen. Deren Kenntnis ist z. B. auch für Altenpflege und klinische Ernährung von großer Bedeutung. Dieser Bericht zeigt aktuelle Ansätze, die Datenlücke bei den (Mikro-)Nährstoffen messtechnisch zu schließen. Die Einsatzfähigkeit dreier Technologien zur Ernährungserhebung insbesondere in Ländern mit Niedrigeinkommen wird diskutiert: die INDDEX24-App, der Automated Ingestion Monitor (AIM) und das Mikro-Spektrometer. Während INDDEX24 bereits implementiert und für AIM eine *free-living* Validierung geplant wird, ist weitere Forschung notwendig, bis Mikro-Spektrometer umfassende Nährstoffanalysen ermöglichen.

Schlagworte: Ernährungserhebung, Niedrigeinkommen, NIR-Spektroskopie, Mineralstoffversorgung, Maschinelles Lernen

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Introduction

One of the major challenges in nutrition science is to accurately measure a person's diet. The most commonly used methods are the prospective weighed food record (WR), used for validation purpose, in addition to the retrospective food frequency questionnaire (FFQ) and 24-h-Recall (24-h-R), which are both suitable for large scale nutrition studies. While the WR puts a high burden on the participants and is shown to influence the eating behaviour due to the reliance on reporting actively (reactivity bias), the two other methods are less accurate and rely on the participants' memory, which can cause recall bias (Buzzard 1998: 56-59, Trabulsi & Schoeller 2001: 892, Schatzkin et al. 2003: 1058).

Moreover, one major known limitation of the 24-h-R is the underreported energy intake in comparison to a reference method (urinary nitrogen and doubly labelled water) (Kroke et al. 1999: 443, Goris et al. 2000:132). Consequently, the methods most commonly used in large scale studies are of limited accuracy. Additionally, for many countries a significant gap occurs, especially around micronutrient intake data (Development Initiatives 2018: 54). Thus, not only is more data required, more important is the need for more precise dietary data. This is needed to investigate combined forms of malnutrition, their consequences for health and diseases and for politicians to target resources and specifically tailor policies to the requirements in the respective country or area (Gillespie et al. 2013: 555, Development Initiatives 2018: 55).

Therefore, an affordable standardized method, able to collect individual dietary data in nationwide surveys on a regular basis, suitable or at least adoptable for different contexts, including low-income countries (LIC), is required. Different approaches are on the way, using innovative technologies for either data collection, data sharing or both (Development Initiatives 2018: 54-88).

This report aims to give insight in the current efforts made in closing the data gap in individual consumption data, with the focus on LIC. Three strategies, which are using different innovations in dietary assessment, are presented and their potential benefits and ability to close the (micro-) nutrient data gap are discussed.

Innovative technologies for dietary assessment in low-income-countries

INDDEX24 – standardize and build the infrastructure for dietary assessment

INDDEX24 is a dietary assessment tool created by the International Dietary Data Expansion (INDDEX) project, a joint project of the Gerald J. and Dorothy R. Friedman School of Nutrition Science and Policy, the Food and Agricultural Organization (FAO) of the United Nations, the International Food Policy Research Institute and other international experts. INDDEX aims to create a standardized approach for the collection and analysis of individual dietary data. The dietary assessment method chosen, is an interviewer administered, technology-assisted 24-h-R for offline use on a tablet, linked to a web application (app). The web app needs to be populated with data inputs required for processing 24-h-R data and tailored to the country/area context of the survey. During the project the INDDEX team will work in close collaboration with two countries to adapt and test the new dietary assessment app. The infrastructural guidance, tools, and databases generated by the project will be transferred to international organizations and implemented in national networks to make them widely accessible beyond the project (INDDEX 2019).

First results of a feasibility testing in Vietnam and Burkina Faso with 60 participants respectively, led to the development of an improved version of INDDEX24 with increased operating speed. Other issues reported were related to the context specific inputs like portion size estimation aids, missing food items or the difficulty of estimating mixed dishes. These are issues always faced regardless of the data collection platform (Colaiezzi et al. 2016).

The INDDEX24 web app aims to support users overcoming these issues by providing excel templates for data input and a search engine to find already existing data for the respective context (INDDEX Project 2019).

In summary, INDDEX uses the innovation of technical-assisted 24-h-R to standardize and facilitate the collection of individual dietary data and the linked web app, to make the method easily adaptable to the specific area/country the data is collected. It sounds promising but no detailed information about the method could be found at the time of writing this report. Coates et al. (2016: 9-16) describe (technical) requirements for INDDEX for the developing or updating of an already existing dietary assessment tool. These are presented in table 1 (see appendix), but it is not clear if they could all be implemented. Moreover, validation studies are needed as well as process evaluation during the implementation period to show if INDDEX really facilitates dietary data assessment, especially in LICs.

AIM-2 – an opportunity to eliminate recall bias

One strategy in optimizing dietary assessment and especially in reducing the participant burden is to automate the process and making it independent from memory. Various wearable technologies like sensors or cameras are included in the review Bell et al. (2017: 925) conducted for INDDEX: They reviewed modern technologies for the collection of food consumption data on individual level, considering the conditions of many LIC contexts. Among other factors, LICs are often constrained by illiteracy, innumeracy, limited internet connectivity, and intermittent electricity. One of the reviewed technologies is the Automatic Ingestion Monitor (AIM), which performs poorly just fulfilling two of the predefined criteria for suitability in LICs. But since the review was done Farooq and Sazonov further developed the method and a 2.0 version of AIM was already tested in a case study in Ghana and will be tested for accuracy of dietary intake assessment versus weighed food intake in two low-and-middle-income countries (LMIC), Ghana and Kenia (Farooq & Sazonov 2017: 3-10, Anderson et al. 2019, McCrory et al. 2019).

In the updated version of AIM the data collection module is connected to the temple of eyeglasses and a camera triggered by the detection of food intake is integrated. The collection module comprises of two sensors a strain sensor pressing against the temporalis muscle to monitor its contractions and an accelerometer that notices subtle movements of the jaw (IEEE Spectrum 2019).

As not all movements of the temporalis muscle and the jaw are related to chewing, AIM needed to be ‘trained’ to differentiate between the sensor signals induced by chewing and those related to other movements. Therefore, Farooq and Sazonov (2017) collected data from ten participants wearing the piezoelectric sensor attached to the temporalis muscle, either in a laboratory situation where they had to do defined activities (rest, eat, talk, walk, walk and eat) or during their normal day-to-day life. The goal is to train a machine learning algorithm to detect chewing bouts even in complex situations. In this study the data collection module contains a button as well, which is used by the participants to mark start- and endpoint of the eating occasion. The leave-one-out-cross-validation-procedure is used to train a support vector machine, resulting in an average F1-score of 96, 28 %, suggesting a high accuracy in detection of food intake even in complex situations. The procedure used by Farooq and Sazonov consists of three stages, the segmentation to identify high energy segments, classification to differentiate between chewing and other activities and the chew-count-estimation stage (Farooq & Sazonov 2017: 3-9).

Handheld near infrared spectrometers – helpful tool in the generation of food composition data

Bell et al. (2017: 926) in their review for INDDEX identify two commercially available handheld spectrometers used for the scanning of food, SCiO and TellSpec, both not fulfilling the predefined criteria for dietary data collection in LIC, but as Bell at al. concludes, promising for the creation of food composition databases (FCDB). The usefulness of handheld spectrometers in food analysis seems to be a controversial issue. On the one hand optical spectroscopy in the near-infrared spectrum can serve as a non-destructive measuring method on foods with immediately available results (Rateni et al. 2017: 19). An affordable (< $500) series production of miniaturized sensors built into light (<100g) instruments is already possible (Consumer Physics 2017, Neves et al. 2019: 1).

Moreover, according to Rateni et al. (2017: 12) micro systems, like SCiO and TellSpec, became a 'black-box', able to provide expected results through databases based on machine learning, with high reliability and without needing technicians. Neves et al. (2019: 1) on the other hand, call the advertising statements for instruments like SCiO and TellSpec 'exaggerated'. They are using the Viavi MicroNIR 1700 (formerly JDSU, Santa Rosa, CA, USA) and an approach different to the cloud based 'big data' approach that the companies promote. For a quantitative analysis of six nutritional parameters (energy, protein, fat, carbohydrates, sugar, fibre) they develop chemometric partial least square models. Therefore, they measure 25 combinations of five different types of pasta with five different types of pasta sauce and five different pasta-to-sauce-ratios, respectively, resulting in 125 'ready-to-eat' pasta-sauce-combinations. The prediction performance is checked using cross validation and test-set-validation. The relative prediction errors are lower, the higher the content of the respective nutrient is. For sugar and fibre, the comparatively large average relative prediction errors of 11.4 % and 18.2 % respectively, are probably due to the structural similarity of these nutrients with carbohydrates, the main component in the dish. For energy and carbohydrate, the average relative prediction errors are 2.7 % and 6.4 %, respectively, for protein 8.3 % and the calibrations for fat led to average relative prediction errors of 16.1 %. Thus Neves et al. summarize that their achieved calibration results show realistically expectable accuracy for the quantification of the analysed nutrients, using handheld spectrometers. The results moreover demonstrate that the "cloud-derived" data, advertised by several direct-to-consumer companies is not realistic, as their food-scanners are relatively simple and therefore cannot achieve high accuracy. Nevertheless, the results they obtain lead them to the conclusion that in the near future nutrient analysis of mixed dishes with handheld spectrometers will be possible on consumer level (Neves et al. 2019: 2-8).

Discussion: Potential benefit of innovative technology for dietary assessment

None of the three methods introduced in chapter two is ready for scaling up nutrition data, especially in LICs, yet. While INDDEX is tested in two countries, is currently updated and then will be hosted at international organisations, accessible for researchers worldwide, the two other methods are still in its infancy and well-planned validation studies are required as well as technical solutions for more precise measurements or other identified challenges. Nevertheless, this report aims to give insight in the current efforts made in closing the data gap in individual consumption data, focussing on LICs, and all three methods could be beneficial regarding dietary assessment in this setting in certain areas of this field. INDDEX24 might reduce misreporting and recall bias: For some food items it is known that they are likely to be forgotten and that portion size estimation is difficult (Moshfegh et al. 2008: 325, Subar et al. 2010: 6).

In the technical assisted 24-h-R memory cues can help to reduce forgotten foods even without decreasing standardization as the software will use the same memory cues for everyone. Moreover, a database of pictures of commonly consumed food items can be integrated easily for identification or pictures of commonly used measurement tools as aids for portion size estimation. Images of portion sizes, especially if different sizes are presented at the same time, or portion size measurement aids can improve accuracy in portion size estimates (Byrd-Bredbenner & Schwartz 2004: 344-355, Subar et al. 2010: 7).

Therefore, INDDEX24 could make food identification and portion size estimation more accurate, if the web app is populated with the respective country-specific picture databases. In general, technical-assisted 24-h-R in comparison to the 'paper-pen-version' can reduce interviewer bias and are less time-consuming during fieldwork and therefore reduce costs (Coates et al. 2016: 13). The use of tablets for data collection seems to be accepted in LIC context (Colaiezzi et al. 2016). Another advantage is, that the collection and codification of data happens in real time and thus less time is required for analysing the data (Liu et al. 2011: 2004). Additionally, the daily intake is automatically calculated, providing a control-tool immediately (Coates et al. 2016: 13).

Lafreniere et al. (2017: 2) emphasize the importance of 'rigorous validation' of new dietary assessment tools, in the best case against objective tools like fully controlled feeding studies or biomarkers. For INDDEX24 no validation studies could be found. Another technical-assisted 24-h-R specifically designed for LMIC, the NINA-DISH, is claimed valid, but only after validation against 'paper-pen' 24-h-R and in a small (N=22) sample size study (Carpenter et al. 2017). Further validation of technical-assisted 24-h-R is required, before using it for large scale surveys in

LIC/LMIC. Even in the less time-consuming technical-assisted version, the 24-h-R takes a lot of time and personnel resources. The interviewers need to be trained in the use of the app and depending on the context in the use of a tablet in general.

A wearable method like AIM would reduce personnel resources. It would shift the necessity of conducting a 24-h-R-interview to explaining the wearable method and discuss privacy issues with the (possible) participants. Participants might be sceptical about the new technology and concerned about their privacy. Therefore, different skills than for a 24-h-R are required, e.g. being empathetic of privacy concerns and addressing them. There are some other limitations: the camera triggered by chewing might not be able to detect snacks that are eaten quickly (very short 'one-bite' eating occasions cannot be documented). Furthermore, as AIM uses a novel method for data collection, it has to be validated in the field. It has been validated in an in-house study (N=40) against the eating occasions identified by trained human raters on the video material from installed cameras in the apartment where the study took place (Farooq et al. 2019: 3-4).

But validation in free-living conditions against weighed food records needs to be carried out. On the positive side, AIM does not rely on memory. The method could be a landmark in reducing participant burden and misreporting due to recall bias or changes in eating behaviour due to the commitment of documentation and/or weighing (reactivity bias). AIM itself just detects chewing bouts, it has to be supplemented by a camera, a visual algorithm to identify food and estimate portion size or a trained dietitian to evaluate the pictures. Moreover, it has to be connected to a FCDB if nutrient estimates are the requested output. The output quality highly relies on all these inputs as well. In summary a lot of work in different research fields needs to be done before AIM would be suitable for the collection of precise dietary data on a large scale. It is questionable, if it is suitable for large scale data collection at all, taking into account the privacy aspects. But as AIM demonstrates different strengths than the 24-h-R, e.g. being objective and not dependent on memory, it could be used for relative validation of dietary assessment methods.

The micro-spectrometers are not fit for use in nationwide nutrition surveys: They do not provide portion size estimates and the technology to estimate nutrient composition had not yet been perfected. The last aspect also applies to their possible use for facilitating the development and updating of FCDB. For the creation of FCDB, calibrations for more than six nutrients (see chapter 2.3) would be required. Even though handheld/micro near infrared spectrometry has shown good results in authentication, classification, quality control and adulteration in food science, and recently is used to develop calibration models to quantify nutritional parameters, in none of these projects (more than six) nutritional parameters are quantified (Santos et al. 2015: 1207, Fardin-Kia et al. 2017: 9-14, Modrono et al. 2017: 597–603, Basri et al. 2018: 4143–4151, Grassi et al. 2018: 382–388, Wiedemair & Huck 2018: 233–240, Neves et al. 2019: 3).

No literature is found on micronutrient calibration. In summary, a lot of work still needs to be done in order to make the handheld spectrometer a reliable and accurate method for the measurement of a variety of nutrients.

Conclusion

The dietary assessment methods named in the introduction part (WR, 24-h-R) are still in use. Technology today allows to collect and process data in real time by shifting the 24-h-R method from the traditional 'paper-pen-version' into a technical-assisted version. There are issues that all "traditional" methods (FFQ, WR, 24-h-R) have in common. The person actively needs to report the consumed food and either weigh or estimate the portion size. Moreover, for (micro-) nutrient estimates all these methods additionally rely on the connected FCDB and other complementing data inputs (e.g. portion conversion). The three introduced innovations focus on one of these issues respectively. While INDDEX aims for standardizing and improving the already widely used procedure of 24-h-R, AIM is chosen as an example of technology trying to automate dietary assessment, make it objective and overcome the problem of recall and reactivity bias. As mentioned above, precision regarding (micro-) nutrient estimates is limited for both methods by the quality of the FCDB. Therefore, the ability of handheld spectrometers to update or even create FCDB in LIC is investigated.

For INDDEX, project evaluation and implementation are underway and for AIM feasibility testing and validation against approved methods (WR) are planned. Results of these studies are needed before a conclusion can be drawn regarding their potential benefits and ability to close the (micro-) nutrient data gap. Handheld spectrometers were presented as a promising tool regarding the updating or even creation of FCDB in LIC. After looking at the evidence however, this conclusion is retracted. The direct-to-consumer companies selling handheld spectrometers make it seem, as if it is already possible to measure nutrient contents of all foods possibly consumed, but scientifically derived models/calibrations are still rare and not available for more than six nutritional parameters. A lot of work is still required until handheld spectrometers can be helpful regarding comprehensive (micro-) nutrient analysis of foods to create/update FCDB in LIC. Nevertheless, the creation of FCDB should not be neglected in the process of filling the data gap, as the quality of (micro-) nutrient data derived from food intake data highly depends on the quality of the FCDB used.

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Autorin

Sara Jansen BSc, Universität Bonn, Landwirtschaftliche Fakultät,

Studiengang Humanernährung

Kontakt: s7sajans@uni-bonn.de

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Tab. 1: Priority criteria and technical specifications for a technology-assisted 24-h-Recall defined by INNDEX technical report committee (modified from Coates et al. 2016: 9-16)

Priority Criteria	Technical details / specification
1. Application suitable for laptop/tablet	• -the software should not require many databases to be open at once
2. Application/data collection must operate offline	• data needs to be stored on the device: (re)initialization and collection and saving of multiple recalls • function to transfer the stored multiple recalls to a centralized database through internet connection
3. Four-stage multiple pass method + Start up	-A „start-up“ is required, where the following information is collected: • Interviewer name • respondent name • sex • ID number • household GPS location • day and date of interview (day/month/year) + via drop-down menus: • if the recall is for a weekday, a weekend day, a market day, or a feast day • whether the day's consumption is representative in relation to the amount of food consumed (e.g., below average, average, and above average) • photos of locally available products of supplements + dosage+ frequency (e.g., daily, weekly, monthly, or never) • photos of locally available medications (e.g., for malaria) • options for drinking water sources →Saved as XLS format file and used as a spreadsheet for each food consumed -24-h-Recall: Pass 1: quick list of foods and dietary supplements consumed (display the quick list in a window on one side of the screen and update it in real-time for review). Pass 2: complete description of each food and beverage (either match each item from the quick list to a description from FAO international food composition database, or search and browse an organized list for approximate matchings, or if nothing similar found free text entry is possible Pass 3: amount of each food (quantity estimation method depending on food type) Pass 4: Review the whole day (changes and additions are possible, missings are highlighted, check for proportionate energy intake is possible)
4. User friendly	• easy language/avoid using professional terms • single-user interface/all activities within a single screen, without overlapping windows, consistency • input sequentially as food was consumed: starting at 0:00 h- ends at 23:59 h, one food at a time, each food as a single record, identified by time of day instead of meals. • navigation panel to map the progress of the interview • 'undo' function, addition of foods in non-sequential order, 'copy and paste'/"same as before" function to enter foods consumed several times in one day • Misspelled words automatically recognized by using correction algorithms (e.g. metaphone algorithm, GoogieSpell). • prompt to record drinks with a meal/review long-periods of time during which no food items are recorded
5. Linked to FCDB	• link to the planned FAO international food composition database via an alpha-numeric code for each food and ingredient consumed. minimal requirements for database search tool: • misspelled words automatically recognized by using correction algorithms, local food names and synonyms are recognized • identify food items that look like multiple items (e.g., fish and chips) and prompt the user to split them into discrete items • enable to choose how search results are displayed: by popularity, alphabetical order, or food groups
6. Customize portion size estimation photographs	• vertical aerial photos with a scale, simultaneously display photos of different portion sizes (seven in total), from fifth to 95th percentile of served weights • or use of commonly available local portion sizes and country specific spoons, cups, plates (for example use database tool in Java to facilitate this)
7. Contexts specific	• overall framework of the program in English • translation to other languages must be integral
8. Post data collection	- common algorithms to • adjust for raw to cooked edible parts • calculate fat absorbed while cooking -standardized method for • conversion of volume to weight • assign food group codes to mixed recipes