18032 Food Friend

Work package 3 – Deliverable 3.1

Nutrition assessment and coaching overview

Responsible partner: Maastricht University

Contributing partners: All partners

Due date of deliverable: M12

Actual submission date: M21

Actual report status: revision 1.0

Project start date: 01.10.2019

Project duration: 48 months

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Participants:

DOCUMENT HISTORY

Revision	Date	Author	Remarks
0.1	14.08.20	Ine Vandewauw	First draft created
0.2	28.08.20		Input partners
0.3	26.05.20		Input all partners
0.4	10.06.20	KU Leuven	Reviewed
1.0	23.06.21	Ine Vandewauw	Submitted

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1 INTRODUCTION

Malnutrition has a negative influence on patient's clinical outcomes, body function, autonomy, and quality of life. In order to start a timely and adequate nutritional support, it is crucial to identify patients at risk of malnutrition or who are malnourished in an early stage. A simple and rapid tool to detect these patients is nutritional risk screening. Patients found to be at risk should subsequently undergo a more detailed assessment of nutritional status to understand the nature and cause of the nutrition-related problem. Based on this nutritional assessment, a personalized nutritional intervention adapted to the individual patient's need should follow. Here, we provide an overview of nutritional screening and assessment methods, and describe technological approaches developed to improve the accuracy of dietary assessment.

2 NUTRITIONAL RISK SCREENING

Nutritional risk screening tools are easy to use, quick, inexpensive, standardised, validated and thus very useful in the daily routine to detect malnutrition. Several screening tools were established for use in various clinical settings and patient populations [1]. We will discuss three examples that are recommended by the European Society for Clinical Nutrition and Metabolism (ESPEN): the Nutritional risk Screening 2002 (NRS-2002) for the inpatient setting, the Malnutrition Universal Screening Tool (MUST) for the ambulatory setting, and the Mini Nutritional Assessment (MNA) for institutionalised geriatric patients. [2] The NRS-2002 (Table 1) is a straightforward and well-validated tool that includes a pre-screening with four questions. If the answer to one of these questions is positive, a screening follows that contains surrogate measures of nutritional status and data on the severity of the disease (stress metabolism). [3] The MUST (Table 2) was developed to identify malnutrition in all care settings, e.g. hospitals, nursing homes, home care, etc. and served as a basis for the NRS-2002. [4] The MNA is used for institutionalised geriatric patients and includes several items often relevant for the nutritional status of elderly, such as loss of appetite, altered sense of taste and smell, loss of thirst, frailty, depression. It also includes anthropometric measurements, nutritional habits, general condition, and self-evaluation. [5] There is also a short-form (MNA-SF) available (Table 3), which only includes six items, but is faster and as effective as the long version. [6]

Table 1. Nutritional Risk Screening 2002. APACHE: acute physiology and chronic health evaluation; BMI: body mass index; COPD: chronic obstructive pulmonary disease; ONS: oral nutritional supplement.

Pre-screening			
Is the BMI of the patient < 20.5 kg/m2			Yes/No
Did the patient lose weight in the past 3 months?			Yes/No
Was the patient's food intake reduced in the past week?			Yes/No
Is the patient critically ill?			Yes/No
If yes to one of those questions, proceed to screening. If no for all answers, the patient should be re-screened weekly.			
Screening			
Nutritional status	score	Stress metabolism (severity of the disease)	score
None	0	None	0
Mild Weight loss >5% in 3 months OR 50–75% of the normal food intake in the last week	1	Mild stress metabolism Patient is mobile Increased protein requirement can be covered with oral nutrition *Hip fracture, chronic disease especially with complications* *e.g., liver cirrhosis, COPD, diabetes, cancer, chronic* *haemodialysis*	1
Moderate Weight loss >5% in 2 months OR BMI 18.5–20.5 kg/m2 AND reduced general condition OR 25–50% of the normal food intake in the last week	2	Moderate stress metabolism Patient is bedridden due to illness Highly increased protein requirement, may be covered with ONS *Stroke, hematologic cancer, severe pneumonia, extended* *abdominal surgery*	2
Severe Weight loss >5% in 1 month OR BMI <18.5 kg/m2 AND reduced general condition OR 0–25% of the normal food intake in the last week	3	Severe stress metabolism Patient is critically ill (intensive care unit) Very strongly increased protein requirement can only be achieved with (par)enteral nutrition *APACHE-II >10, bone marrow transplantation, head* *traumas*	3
Total (A)		Total (B)	
Age			
<70 years: 0 pt ≥70 years: 1 pt			
TOTAL = (A) + (B) + Age			
≥3 points: patient is at nutritional risk. Nutritional care plan should be set up <3 points: repeat screening weekly			

Table 2. Malnutrition Universal Screening Tool.

Malnutrition Universal Screening Tool (MUST)					
BMI (kg/m2)		Unintentional weight loss in the past 3–6 months		Acute illness with reduced food intake (estimated) for ≥5 days	
≥20	0	≤5%	0	No = 0	
18.5-20.0	1	5-10%	1	Yes = 2	
≤18.5	2	≥10%	2		

Overall Risk for Malnutrition			
Total	Risk	Procedure	Implementation
0	Low	Routine clinical care	<u>Clinic</u>: weekly <u>Nursing home</u>: monthly <u>Outpatient</u>: yearly in at-risk patient groups, e.g., age >75 years
1	Medium	Observe	<u>Clinic, nursing home, and outpatient</u>: Document dietary intake for 3 days. If adequate: little concern and repeat screening (hospital weekly, care home at least monthly, community at least every 2–3 months). If inadequate: clinical concern. Follow local policy, set goals, improve and increase overall nutritional intake, monitor and review care plan regularly.
≥2	High	Treat	<u>Clinic, nursing home, and outpatient</u>: Refer to dietitian, Nutritional Support Team, or implement local policy. Set goals, improve and increase overall nutritional intake. Monitor and review care plan (hospital weekly, care home monthly, community monthly).

Table 3. Mini Nutritional Assessment Short-Form.

Screening		
A	Has food intake declined over the past 3 months due to loss of appetite, digestive problems, or chewing or swallowing difficulties?	0 = severe decrease in food intake 1 = moderate decrease in food intake 2 = no decrease in food intake
B	Weight loss during the last 3 months	0 = weight loss greater than 3 kg 1 = does not know 2 = weight loss between 1 and 3 kg 3 = no weight loss
C	Mobility	0 = bedridden or chair bound 1 = able to get out of bed/chair but does not go out 2 = goes out
D	Has the patient suffered psychological stress or acute disease in the past 3 months?	0 = yes 2 = no

E	Neuropsychological problems	0 = severe dementia or depression 1 = mild dementia 2 = no psychological problems
F1	Body mass index (BMI)	0 = BMI less than 19 1 = BMI 19 to less than 21 2 = BMI 21 to less than 23 3 = BMI 23 or greater
If BMI is not available, replace question F1 with F2. Do not answer F2 if F1 is already completed.		
F2	Calf circumference (CC) in cm	0 = CC less than 31 3 = CC 31 or greater
Screening Score		
12-14 points	Normal nutritional status	
8-11 points	At risk of malnutrition	
0-7 points	Malnourished	

3 Nutritional assessment

When, according to the initial screening, a patient is identified as at nutritional risk, a nutritional assessment should be performed, determining the exact problem and its severity. Below, we describe several items that should be part of the nutritional assessment process and the technologies used to measure them. Most of these items have limited sensitivity and specificity when used individually. Therefore, methods to identify malnourished patients require the use of several parameters and the clinical judgement of experienced and specialised clinical staff.

3.1 Clinical evaluation

Patient clinical history

The clinical history of a patient includes previous medical conditions, as well as the actual functional capacity and physiological changes that can influence nutritional requirements. Factors leading to malnutrition, such as pain, gastrointestinal symptoms, inability to chew or swallow, etc. are discussed with the patient. Additionally, cognitive changes affecting appetite and ability to feed oneself may negatively impact the dietary intake. In addition, a patient’s prescribed medication should be examined regarding potential drug-nutrient interactions and nutrition-related side effects.

Physical examination

A physical examination includes the control of vital parameters, the inspection for water retention and a rough assessment of muscle mass and subcutaneous fat. It can detect symptoms of nutritional deficiencies (e.g. poor muscle control, night vision impairment, vertical lip cracks) and assess tolerance to nutritional support (e.g. abdominal distention, vomiting, diarrhoea). [7] Some symptoms are specific for a certain disease or nutrient deficiency, while others are non-specific and need further tests to reveal their aetiology.

Physical function

Energy deficiency reduces muscle strength and power, as well as overall physical condition. Muscle function tests are very sensitive to nutritional deficiencies and changes can be noticed much earlier than through body composition tests. Hand dynamometry (Fig. 1) is a validated method and correlates very well with nutritional status. [8] It is an easy, quick and cheap test, but largely depends on the patient's cooperation. Other functional measurement are knee extension, hip flexion strength, peak expiratory flow, or distance walked in a given time. [9]

Fig. 1. Hand dynameter. (photo credits: hva.nl)

3.2 ANTHROPOMETRIC MEASUREMENTS AND BODY COMPOSITION

Body composition describes the body compartments, such as fat mass, fat-free mass, muscle mass, and bone mineral mass, and can change due to disease, age, physical activity, and starvation. Body composition measurements can serve as an early diagnostic tool, as quantification, or as follow-up method to assess nutritional status.

Body weight and body mass index

Body weight, height, and the resulting BMI are important parameters that are relatively easy to obtain from patients. In order to obtain a reliable weight trend, body weight measurements should be standardised, e.g. measured at the same time of day and with the same amount of light clothing. The BMI is an indicator of chronic malnutrition. Europeans are considered underweight when their BMI is less than 18.5 kg/m^2. In older adults, the cut-off is higher – less than 22 kg/m^2 – as carrying some extra weight seems to be protective in this population. However, BMI may be biased by fluid overload and oedemas, and does not describe body composition (e.g., both fat individuals and muscular athletes can have a high BMI). [10]

Skinfold and circumference measurements

An easy, cheap and non-invasive method to determine body composition is measuring limb circumference and skinfold thickness (SFT). Since subcutaneous fat tissues account for half of the entire body fat mass, measurement of the SFT gives information on the energy stores (mainly fat stores) of the body. To estimate the total amount of body fat, four skinfolds need to be measured: biceps skinfold (front side middle upper arm) (Fig. 2), triceps skinfold (backside middle upper arm), subscapular skinfold (under the lowest point of the shoulder blade), and the suprailiac skinfold (above the upper bone of the hip). [11] These measurements require trained staff and there is a high inter-individual variability, since age, gender, and ethnicity are known to influence the fat mass. Moreover, measurements are less reliable in elderly people, due to their weak skin and muscles. As a result, their muscles are often taken in the skinfold. Also in patients with chronic muscle diseases, dehydration and oedema, skinfold measurements can give unreliable results.

Fig. 2. A skinfold calliper measuring the biceps skinfold. (photo credits: nutritionalassessment.mumc.nl)

The mid-upper-arm muscle circumference (MAMC) reflects the muscle mass, while the mid-arm muscle area (MAMA) gives information about the muscle protein stores, as half of the body's proteins are stored in the skeletal muscles. The MAMA is calculated from the MAMC and the triceps SFT (MAMA = MAMC - (0.314 x SFT)). This method is not reliable in patients with fluid overload and does not represent short-term modifications of the nutritional status. [10]

Bioelectrical impedance analysis

Bioelectrical impedance analysis (BIA) is a simple, inexpensive, non-invasive method that relies on the conduction of an alternating electrical current by the human body. Current can pass easily through tissues containing a lot of water and electrolytes, like blood and muscles, whereas fat tissues, air, and bone are harder to pass through. After correcting for age, sex, and ethnicity, BIA gives information about total body water, body cell mass, and fat mass. BIA is not recommended for patients with fluid overload or extreme BMI, for intensive care unit patients, or for elderly. [12, 13]

Dual energy X-ray absorptiometry

Dual energy X-ray absorptiometry (DXA) depends on radiological density analysis and is an indirect method to determine fat mass, fat-free mass, and bone mineral mass. [14] The principle of DXA is that the attenuation of the X-rays with high and low photon energies is measurable and depends on the properties of the underlying tissue. Despite some exposure to radiation, it is more and more used in research and clinical practice.

Magnetic resonance imaging and computed tomography

Magnetic resonance imaging (MRI) and computed tomography (CT) allow the quantification of fat mass and fat-free mass, give information about the fat distribution and enable an estimation of skeletal muscle mass. Unlike CT, MRT does not require ionising radiation. They are mainly used in research because of their limited availability, costs and time consumed. [15] However, when scans are taken for general diagnostic purposes, they can be used to obtain nutritional information.

Other methods

Other methods are mainly used for research purposes due to their complexity and high costs. These include air displacement plethysmography (ADP), dilution methods, the measurement of total body potassium, and in vivo neutron activation analysis. [10, 16] ADP can determine body density and is based on the determination of body volume by means of air displacement having regard to the residual air volume in the lungs and the gastrointestinal tract. As the density of fat differs from the density of fat-free mass, they can both be determined using a two-compartment model. Dilution methods can determinate total body water by means of dilution of non-radioactive isotopes (e.g. deuterium). Tracers are given orally or parenterally and their concentrations in urine and blood are measured after a given time. Extracellular water can be determined using bromide or sulphate, allowing the definition of intracellular water. Since potassium is mostly found intracellularly and the natural isotope K^{40} is present in constant fraction, the measurement of the potassium allows the calculation of the body cell mass and thus enables the very accurate determination of the body cell mass. With the in vivo neutron activation, the body is irradiated with neutron radiation, inducing the emission of a characteristic spectrum of gamma-radiations. This expensive method allows the quantification of single elements such as nitrogen, calcium, sodium, etc.

3.3 Biochemical analysis

Several laboratory parameters used in the clinical routine (e.g. blood count, lipid profile, electrolytes, liver parameter) may provide valuable information about a patient's nutritional status, changes in body composition, and disease severity. Laboratory values can also help to detect vitamin and trace elements deficiencies and monitor current substitution therapies. [17] However, biochemical analyses are mostly delayed, expensive and largely dependent on the analytics method and the analysing laboratory.

3.4 Dietary intake

A crucial part of nutritional assessment is determining the food intake, including qualitative and quantitative aspects. Both the assessment of macronutrients (proteins, carbohydrates, fat) and micronutrients (vitamins, trace elements) is important. The comparison between food intake and energy expenditure reflects the current nutritional status and determines whether the patient's dietary intake is sufficient or not. The accurate assessment of food intake is difficult and error-prone and there is a growing need for more accurate dietary assessment methods.

3.4.1 Manual dietary assessment

There are several methods to monitor food intake by self-report on paper. These pen-and-paper tools require a lot of manual input and are therefore work-intensive and time-consuming, which often discourages people. Moreover, these methods rely on the information being stored in the memory and the individual being able or willing to report these details accurately. Consequently, data are influenced by biases such as recall bias and social desirability bias and are often incomplete or incorrect. [18-20]

Estimated food diaries

Estimated food diaries are detailed assessment methods that provide good estimates of energy intake and most nutrients, foods and food groups. Individuals record details of foods and beverages consumed at the time of consumption. Portion sizes should be estimated as accurately as possible by the respondents, using common unit sizes (e.g. cups of drinks, slices of bread). Several days of recording are necessary because of daily variations in what people eat. However, the more number of days, the less accurate because of study fatigue. [20]

Weighed food diaries

Weighed food diaries provide descriptions of the foods consumed and eating occasions. Moreover, measurements involve respondents weighing every item of food and drink consumed at the time of consumption, and therefore does not rely on portion size estimation. This method is very labour-intensive, time-consuming, and weighing and recording food eaten away from home can be difficult. [20]

24-hour dietary recall

The 24-hour dietary recall assesses food and beverage consumption during the preceding 24 hours. Multiple recalls are essential to capture habitual consumption of foods. A strength of this method is that the participant’s burden is relatively low. [20]

Food frequency questionnaires

Food frequency questionnaires are designed to assess habitual diet by asking about the frequency with which food items or specific food groups are consumed over a reference period. This method imposes a low burden on the participant and is relatively easy. However, reported intake is limited to the foods contained in the food list. [20]

Dietary checklists

Dietary checklists require the respondents to examine a list of foods and cross-tabulate with attributes such as specified serving size or frequency of consumption, ticking the appropriate box. This method has a low participant burden, but is not useful to capture detailed dietary habits. [20]

3.4.2 Computer-aided assessment

Computerised/smartphone app versions of traditional pen-and-paper methods

These technologies have the same aim as the paper-based methods of dietary assessment and can be web-based or make use of smartphone applications. However, they aim to be more user-friendly and less time-consuming, thereby improving compliance of participants. Another advantage over the traditional paper methods is that calculations on ingested calories can be performed automatically. However, users still have to manually record their food intake and therefore it does not make the data collection process easier. Several systems incorporate some degree of automation, such as barcode readers to automatically recognise packaged food labels. In addition, the inaccuracy of the food intake estimation remains a problem and some population subgroups (e.g. elderly) may face difficulty to use these tools due to the need of computer literacy. Some examples of ‘static’ computerised technologies are ASA24 [21], Intake24 [22], and Oxford WebQ [23]. Examples of mobile application technologies are myfood24 (Fig. 3) [24], Lose it! [25], and Lifesum [26].

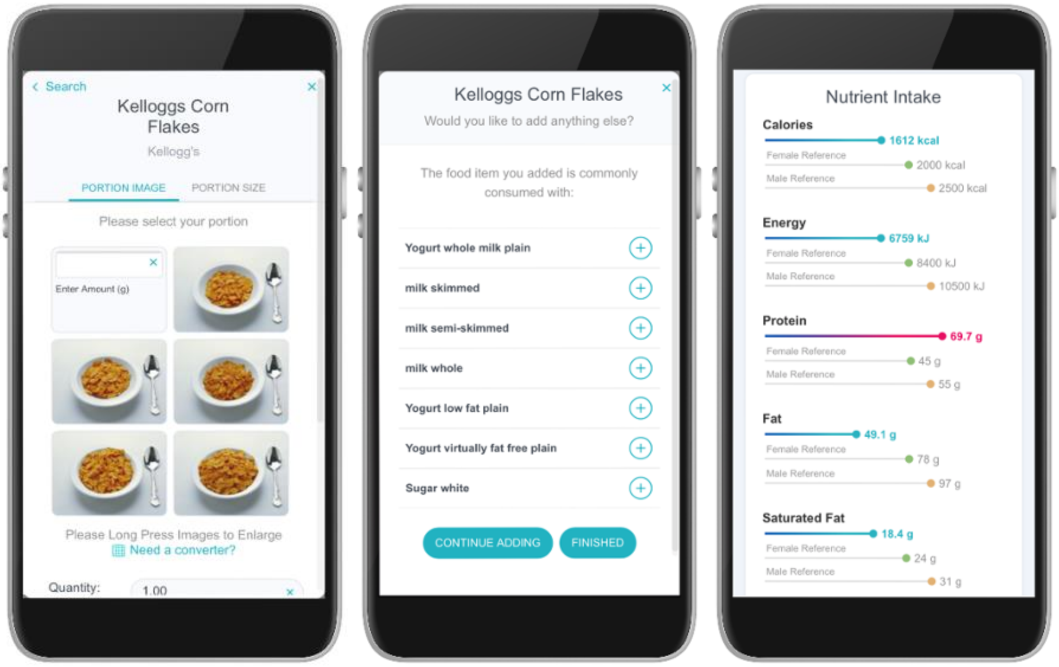


Fig. 3. Smartphone application myfood24. [24]

Computerised/smartphone apps that capture additional raw data

Technologies with automated data capturing and coding systems have the potential to overcome the inherent limitations of traditional methods, such as limited accuracy, participant's burden related to dietary assessment and data entry, dependency on memory, ability and perception of social desirability. These methods are based on capturing images before and after eating episodes to provide primary records of dietary intake instead of manual recording. [27]

Several smartphone apps use digital food photography to assist the dietary assessment as advancement to the traditional methods. The user has to take pictures before and after eating to provide primary records of dietary intake instead of manual recording. These data are then send to the dietitian who analysis the data using standardised methods to estimate the corresponding amount of nutrients. For better estimation of colour and portion size by experts, participants use a fiducial marker, a reference item such as pen or colour checkerboard placed within the camera frame. These methods allow for real time data collection, reduce participant's burden and improve reliability compared to traditional methods. However, poor quality photos and technical problems could hamper data collection. Examples of such systems are the Remote Food Photography Method (Fig. 4) [28], Recaller app [29], and Nutricam [30].

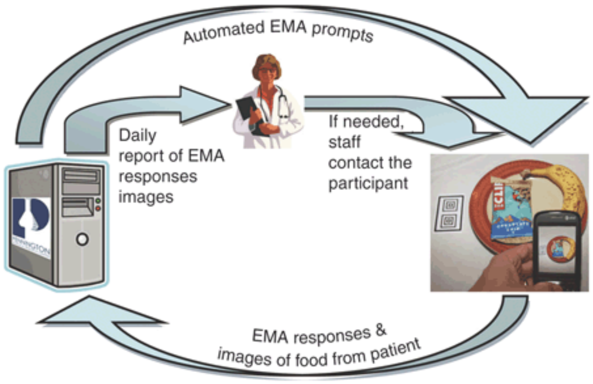


Fig. 4. The Remote Food Photography Method (RFPM) uses ecological momentary assessment (EMA) methods to improve data quality and minimize missing data. Prompts are automatically sent to participants' Smartphones to remind them to capture images of their foods and to send these images to the research staff (the images are received by, and managed in, a computer program called the Food Photography Application). The Food Photography Application also stores responses to the prompts, and it sends automated reports to the research team and they can quickly identify when data acquisition problems occur. [28]

The advanced version of these systems are smartphone applications that integrate the automatic recognition of food items, based on artificial intelligence. The system automatically and in real-time identifies the different food items from the images, recognises the type of food, and creates a 3D model of each of them for volume estimation. Supported by food composition databases, food images are translated into nutrient values such as grams of macronutrients or calories. Examples are mobile device food record [27], snap-n'-eat [31], and DietCam (Fig. 5) [32]. With the ongoing advance of smartphones, as well as camera and image processing, this approach is getting more and more attention in the field of automatic food intake monitoring. Digital photography of food can also be used in cafeteria settings to perform the analysis of nutrients and daily calories consumed by clients. [33] For this, digital video cameras can be placed in the environment, capturing images of people food selection and food remaining on the plate.

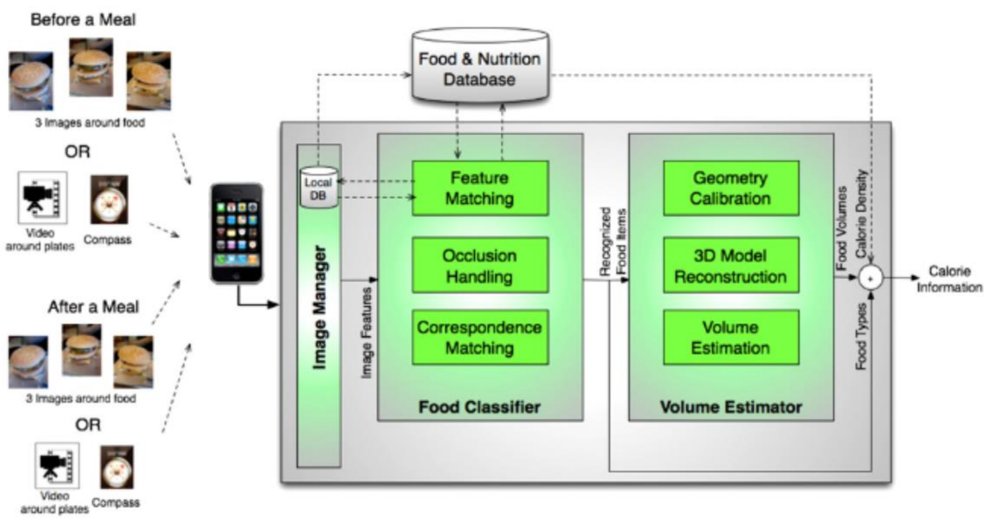


Fig. 5. System architecture of DietCam. The types of food in a meal are classified by the food classifier. The volume of every food item is generated by the volume estimator. [32]

There are also systems where capturing images is automated [34-36]. In this method, participant's wear a camera on a lanyard around the neck. Connected to the smartphone, every so many times an image is captures, so it allows near-complete documentation of food and beverages consumed. This may avoid forgetting or deciding not to include unfavourable food. However, there is need for positioning and technical stability.

3.4.3 Wearable devices

Wearables can directly measure eating behaviour in order to complement self-reporting of nutrient intake. [37]

Detection of chewing and swallowing

Chewing generates sounds that conduct through mandible, skull and body tissue, and can be detected by wearable systems, such as acoustic ear-attached microphones or acoustic ear-pad sensors to capture the vibrations of food chewing. [38-42] There are specialised algorithms to detect and characterise food intake activity based on chewing sounds. Although they achieved acceptable results for single meal experiments in laboratory settings, they have not yet been evaluated in real settings. Swallowing detection is basically parallel to chewing detection, since swallowing is the next phase of chewing in mechanical digestion. [43, 44] Disadvantages of this method are that they recognise only a very limited number of foods and do not provide information on the caloric intake. Moreover, they are often uncomfortable to wear.

Fig. 6. First wearable version of the SPLENDID eating detection sensor (left: the eating detection sensor; rith: the eating detection sensor and datalogger). [42]

Besides an acoustic approach, swallowing events can also be detected by a piezoelectric approach, whereby a piezoelectric sensor is embedded in a wireless necklace or chest belt. [45, 46] These systems are based on the key observation that a person's otherwise continuous breathing process is interrupted by a short apnoea when they swallow as part of the solid or liquid intake process.

In addition, also a physiological approach can be used to detect chewing or swallowing events and comprises two main sensor types: electroglottography (EGG) and electromyography (EMG). The EGG sensor utilises the motion-induced variations of the electrical impedance between two electrodes positioned on the larynx. [47] The EMG sensor can record chewing activity by monitoring the masseter and temporalis muscle activation. [48] Because these muscles are located in exposed facial regions, sensing jaw movement – which is highly variable during chewing and other motions, such as speaking – require attaching a sensor in exposed facial regions.

Detection of eating gestures

Several wearables target the motion of the eating process, especially wrist motion, since eating goes along with the gesturing of hands. Inertial sensors such as accelerometers and gyroscopes can be used to detect and quantify characteristic hand-to-mouth gestures associated with food and beverage consumption. (Fig. 7) [49-51] This technology offers advantages in terms of detecting the timing and amounts of eating behaviour in an unobtrusive, accessible and affordable way that yields high levels of technology acceptance. Disadvantages, including the limited ability to detect brief snacks and the type and amounts of food being consumed, can be addressed by combining these sensors with other active (e.g. self-reporting with a food record or recall) and passive capture methods (e.g. microphone, video).

Fig. 7. Bite-counting device worn on the wrist in 'time' mode. [51]

3.4.4 Smart home

Automatic acquisition of nutritional habits based on ambient intelligence techniques can support the nutritionist by providing an estimation of the nutritional habits of the user using smart home technologies. These make use of sensors for example magnetic contacts in shelves, fridge, drawers, home automation sensors to detect the use of home devices, flow meter to detect when water is flowing through faucet, etc. There are also household appliances that present an application for a smart household appliance. [52, 53] Examples are a smart fridge with multimedia capability designed for managing items stored in it and advising its users with cooking methods depending on what kind of food is stored, or sensors embedded in kitchenware (Fig. 8). [54, 55]

Fig. 8. Smart plate system. [54]

3.4.5 Other

Voice-based mobile nutrition monitoring system that integrates speech processing, natural language processing and text mining techniques in a unified platform. [56] Spoken data is converted to text and, within this text, nutrition-specific data are identified. This information is combined with a tiered matching algorithm to search food names in a nutrition database and accurately compute different intake values (e.g. calories).

Systems that use shopping receipts to generate suggestions about healthier food items that could help to supplement missing nutrients. This system consists of three major stages. [57] First, receipts are scanned in and passed through am optical character recognition program, second, data from this program is passed to database system that records historical information and stores important nutritional information about foods and nutrients. The third component of the system is an inferencing system that estimates what the user eats on average per week and compares this to recommended nutrient consumption. However, this system cannot perform a monitoring for each food intake.

3.4.6 Advantages and limitations of new technologies

These new technologies have several advantages. They are (mostly) independent of memory; they are based on a number of automatic data-processing steps, thus minimising user-related variability; and there is minimal participant burden. Additionally, these technologies offer portability and greater social acceptability than paper-based methods. Some additional advantages include decreased workload, minimisation of researcher's transcription errors and reduced paper waste. [10]

However, each technology also has its limitations. Body sensor monitoring provides no information about the type or quality of the food. What is more, dietitian-supported assessment is labour-intense and expensive to analyse. Moreover, with the AI-based systems, it is not possible to capture all the basic nutrient information (including cooking methods) with one single image. In addition, some food types such as mixed foods or liquids are difficult to analyse with automated image analysis. Other possible disadvantages are incorrect reporting due to poor image quality or user negligence in taking an adequate number of pictures. The most important limitation of most of these technologies is the need for a tech-savvy user. Smart home systems often require an extensive adaptation, infrastructure and measurements can only take place at the installation location. [10]

3.5 Energy requirements

Energy requirements depend upon the energy expended. Total energy expenditure refers to the total amount of energy expended, and contains three main components: resting energy expenditure, thermic effect of food, and activity energy expenditure. [58] The largest portion of the total energy expenditure is the resting energy expenditure, which is the energy needed to maintain basic metabolic activities, such as maintaining body temperature and functioning of vital organs. The activity energy expenditure is the most variable, both at interpersonal as intrapersonal level. Factors that influence the activity energy expenditure include intensity, duration and frequency of activity. Thermic effect of food, also referred to as diet-induced thermogenesis, is the energy required for food digestion, absorption, transport and metabolism, storage of nutrients, and elimination of waste. There are several methods to assess physical activity and energy expenditure, each with its advantages and limitations. [58, 59]

3.5.1 Predictive equations

Energy requirements can be calculated from the basal energy requirement multiplied by an activity factor. Resting metabolic rate relates to characteristics such as body weight, age, gender, and height. These relations have been exploited to generate predictive equations (e.g. the Harris-Benedict formula). [60, 61] These formulae are easy to apply and inexpensive, although the selection of an appropriate equation is a big issue and the results are not very accurate at individual level.

3.5.2 Direct calorimetry

Direct calorimetry is based on the principle that energy spent in all physiological processes is ultimately dissipated as heat. Total energy expenditure can thus be determined by directly measuring sensible heat released by the body, as well as the water steam released through respiration and skin. [62] It requires an isolation chamber that is hermetically sealed, highly sophisticated and large enough to allow some degree of activity. Besides the complex design of the chamber, also other limitations prevent direct calorimetry from being the mainstream method to measure energy expenditure. For instance, due to the heat capacity of the human body and slow heat exchange, whole-room direct calorimetry is not able to detect acute changes in energy expenditure. Moreover, it requires the participant’s confinement of 24 hours or more in a small space. [59]

Advances in wearable technology have led to rekindled interest in direct calorimetry, making it more user-friendly in free-living conditions. Armband-like devices have been developed to detect skin temperature, heat flux, and evaporative heat loss from the skin's surface. [63, 64] Initial results showed that these devices accurately estimate energy expenditure, although ambient temperatures outside the thermo-neutral zone and intense physical activity appear to affect the accuracy of the measurements. [59]

3.5.3 Indirect calorimetry

As the name implies, indirect calorimetry is based on the indirect measure of heat expended by nutrients oxidation, which is estimated by monitoring oxygen consumption and carbon dioxide production. The ratio of oxygen consumption to carbon dioxide production also gives information on carbohydrate and fat oxidation. This means that, in addition to measuring the metabolic rate, it also provides information on the metabolic fuels being combusted. Another advantage is that it allows short-term measurements due to the scarce oxygen body reservoirs and the limited capacity of the body of anaerobic ATP synthesis. Moreover, indirect calorimetry is non-invasive, very accurate and has high reproducibility. It is therefore considered as a gold standard to determine energy expenditure. However, it is quite costly, relatively complex and requires trained personnel for its correct use. Indirect calorimetry can be performed in whole-room respiratory chambers, or by using metabolic carts. [65, 66]

Whole-room respiratory chambers are commonly implemented in metabolic research facilities across the world. Typically, it involves inputs of air with known gas composition into an airtight chamber and continuous sampling of the outflowing air, to allow accurate measurement of oxygen and carbon dioxide concentrations. Whole-room respiratory chambers allow continuous measurement of total daily energy expenditure up to several days. [59]

Measuring resting metabolic rate using metabolic carts in combination with an estimated physical activity level provide an estimate of the total daily energy expenditure that is feasible in most clinical settings (Fig. 9). In contrast to whole-room respiratory chambers that have several limitations, metabolic carts use a facemask, mouthpiece, hood, or canopy to capture exhaled gas, which are connected to analysers mounted on mobile carts. [59]

Fig. 9. Indirect calorimetry using a metabolic cart in combination with a hood. [67]

3.5.4 Doubly labelled water

Using doubly labelled water (DLW) to measure energy expenditure has become the gold standard for long-term free-living measurements. Participants are dosed with water containing known amounts of non-radioactive isotopes of hydrogen (^{2}H) and oxygen (^{18}O). These isotopes equilibrate with hydrogen and oxygen in the body water, and subsequently, ^{2}H exits the body as water and ^{18}O exits the body as both water and carbon dioxide. Turnover rates of ^{2}H and ^{18}O are determined by quantifying isotope concentrations in body fluids (most commonly urine) using mass spectrometry and the differential disappearance of the two isotopes provides a measure of carbon dioxide production, allowing the calculation of energy expenditure. DLW can be used to measure total energy expenditure over 4-21 days, with spot urine samples collected immediately prior to dosing and daily or weekly thereafter. [68, 69] The DLW method has a high accuracy, is non-invasive, and has the possibility for participants to continue their normal activities during the measurement period, since there are no limitations of confined space or gaseous sampling attachment. The disadvantages of this method are that there are numerous assumptions involved in the calculations, which may compromise validity of the measurements, the high costs of the isotopes, the expensive equipment and the expertise required for analysis. [69, 70]

3.5.5 Kinematic measurements

To estimate the activity energy expenditure is necessary to know the movement of free-living individuals. This is typically measured using pedometers and accelerometers. [58] Pedometers are motion sensors that respond to oscillations in the acceleration of the body segment (hip, thigh, wrist, etc.) during gait cycles, providing output as an accumulated step count. They only measure walking or running activity and do not capture activities such as cycling, swimming, weight lifting, etc. Moreover, pedometers are not able to assess the intensity, frequency or duration of the physical activity. The main advantage of pedometers is their low cost. [71]

Accelerometers can detect body displacement by measuring the acceleration of the body in one, two, or three planes (uniaxial, biaxial, triaxial) and generate an output in the form of counts per unit time. These can be converted in energy expenditure using predictive equations, however this is not always practical and can cause significant errors. [72] Acceleration measurements can be used to gather information about duration, frequency and intensity of physical activity. Technological advances have resulted in accelerometers that measure accurate and are sufficiently compact and discrete for people to wear. However, hardware attachments and adhesives may cause skin irritations and some devices are not waterproof and need to be removed prior to swimming, resulting in non-wear time/missing data. The complex relationship between movement and energy expenditure, which needs to take into account variables like gender, age, body mass, and efficiency of movement, implicate there is no simple solution to accurately predicting energy expenditure from any kind of physical activity measurement. [71, 73]

3.5.6 Heart rate monitoring

The use of heart rate monitors to measure activity energy expenditure is based on the assumed relationship between heart rate, activity intensity and oxygen consumption. However, there is considerable inter- and intra-individual variation in this relationship. Differences are mainly related to factors such as age, gender, type of activity, physical fitness, but also to factors such as ambient temperature, dehydration, illness or emotional stress. Chest strap monitors must be well fitted in order to provide contact with the skin, this may be uncomfortable when measuring heart rate over several days. Alternatively, ECG electrodes can be used; however, these can have problems with placement and lead to skin irritation. Despite these limitations, heart rate monitors remain popular as they present advantages of relatively low cost, non-invasive nature and versatility. [58, 59]

3.6 Quality of life

A more subjective parameter that is becoming more important in a nutritional assessment, is the quality of life. It gives an idea about the current health status and may be used as an outcome parameter to monitor nutritional therapy. It is based on the perception of wellbeing in several areas, such as symptoms (pain), physical (mobility, strength), psychological (anxiety, depression), and social (isolation), all potentially having an effect on eating. There are many questionnaires available, but there is no consensus on which should preferably be used. [10]

4 OBESITY CASE AND CORPORATE WELLNESS

Obesity & Wellness Applications

Obesity & Wellness applications, by design, aim to support users on sustaining a healthy lifestyle. Main purpose of these applications are to support healthy behaviours rather than preventing illness. Some of the applications in this category make extensive use of gamification technologies. Common application strategies are focuses on diet and exercise and they track user behaviour through digital diaries.

One of the specific application areas of obesity management and wellness targets corporate wellness applications.

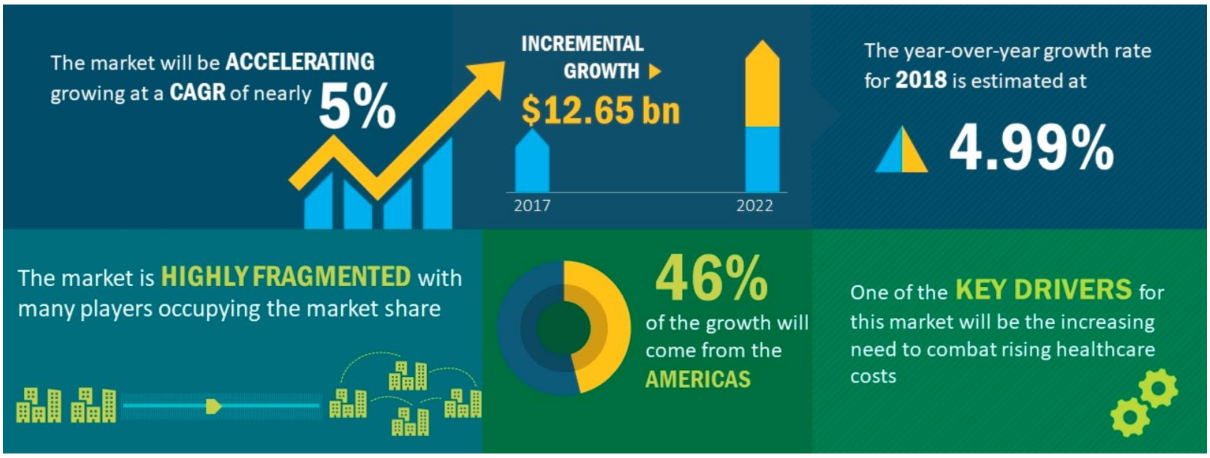
4.1 CORPORATE WELLNESS MARKET

It is expected that the global corporate wellness applications market will reach $97.4 billion in 2027 with CAGR % 6.9. Costs based on the increasing working tempo of employees in corporate companies underlies the expected figures.

Corporate wellness applications especially focuses on topics such as, Stress management, Obesity, Smoking, Unhealthy food consumption, insufficient physical activities.

To increase the productivity of employees, many corporations are starting their own corporate wellness programs for their employees. Some companies delivers hardware to their employees such as FitBit smart watches, Apple and Google smart watches to track information such as blood pressure.

Research indicates that the North America region leads in terms penetration of corporate wellness applications. Around 80% of corporation has a corporate wellness program for their employees.



Mobile application helps to increase the penetration of wellness applications for individuals, and plays an important role for the growth of corporate wellness market.

A survey conducted in 208 by PWC, shows that around half (49%) of the Americans uses a wearable health device. Expectation from these devices are;

- 70% - Healthier and longer living
- 63% - Healthy weight control
- 62% - Paying less insurance fee

Especially the last items shows the importance of mobile applications in the vertical markets. These kind of platforms provides a basis to integrate various service categories such as insurance, mCommerce.

4.2 Existing Recommendation Systems

	ARD Recommendation System	Existing Systems
Demographic Data	Yes	Yes
Eating Activity	Yes	No
Daily Energy Data	Yes	No
Daily Food Intake Amount	Yes	No
Food Ingredients	Yes	Yes
Goal Data	Yes	Yes
Healthy Living Recommendations	Yes	Yes
Health Data	Yes	No

Obesity Data	Yes	Yes
Personal Recommendation Engine	Yes	No
Media Support	No	Yes
Family Doctor Support	No	Yes

https://iopscience.iop.org/article/10.1088/0967-3334/33/6/1073

https://ieeexplore.ieee.org/abstract/document/6601618

https://ieeexplore.ieee.org/abstract/document/6200559

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http://www.diabetcemiyeti.org/c/turkiye-saglikli-beslenme-ve-hareketli-hayat-programi

https://www.saglikliturkiye.org/projeler/obezite-program/

http://heygenchareketegec.com/

https://29mayisdh.saglik.gov.tr/TR,331048/obezitenin-tibbi-beslenme-tedavisinde-guncel-egilimler-egitim-programi-projesi.html

4.3 Mobile Application Libraries

ResearchKit

Is an open source SDK which is supported by Apple. It is used to get medical information of users. It provides the infrastructure to receive data such as; length, weight, glucose values.

CareKit

It is a SDK that gives that helps users to understand and manage their health status. It can track certain health trends, identify goals and corresponding strategies to reach these goals. It can also helps to give incentives to reach the goals.

Happitech

Is a SDK that measures data such as, heartbeat, stress, physical condition, heartbeat anomalies.

Binah.AI

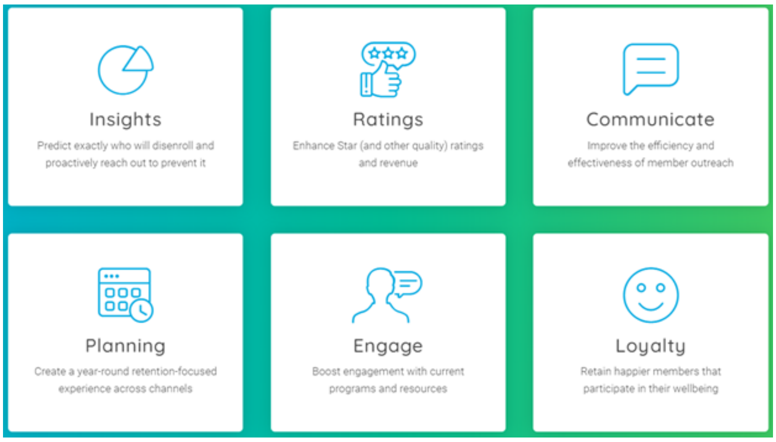
Is a SDK to measure PPG through a mobile phone camera. SDK also measures heart rate, oxygen saturation, HRV, and stress index.

4.4 3.7.4 Mobile Application Solutions

Welltok - https://welltok.com/

Well tok application focuses on corporate wellness and has a data focused approach. Aim of the application is to provide added value to employees through the wellness applications while providing information to employers about the gains of the overall program.

Application provides personalized recommendations and programs to individual employees. Application tracks the user activities after recommendation through gamification and reward mechanisms.



Circle Care - https://www.mycirclecare.com/corporate-wellness-app/

While targeting to increase the physical life quality of employees, the application also targets higher involvement of employees in the company culture and increased productivity. A web application provides a dashboard module to the company executives, while employees reaches via the mobile application.

Several goals such as number of steps, daily water consumption assigned to users and support with gamification and rewarding mechanisms.

Hot Seat - https://www.gethotseatapp.com/

Aims to measure the physical activities of corporate employees. Application uses notifications to remind users to give breaks or take some exercise to complete targeted daily goals.

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