INNOVATIVE NUTRITIONAL DIGITAL BIOMARKERS BASED ON ACTIMETRIC BEHAVIOR MONITORING

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ABSTRACT

Older people represent a large part of the population. Focusing on this population in order to protect them from the health risks they may face during their lifetime, especially undernutrition, is a very important issue. Indeed, undernutrition is a disease state caused by an imbalance in nutritional intake in relation to the body's energy expenditure. With technological advances, biomarker measurement has become more efficient and specific, allowing us to better diagnose undernutrition in the elderly. This article presents a large study on healthy aging. Patients use a mobile application called ICOPE to screen for undernutrition and obtain biological data coupled with digital biomarkers obtained from a system for measuring lifestyle behavioral parameters. Actimetric measurements could be considered as a 'partial' parameter to be integrated with others, closer to physiological conditions.

KEYWORDS

Undernutrition, Biological Biomarkers, Digital Biomarkers, Elderly, Life Habits Monitoring, Health Data

1. INTRODUCTION

Worldwide, people aged 65 and over living alone represent a significant proportion of the population in the US (13%) and France (19.6%) (Piau, 2019). In our study, we are interested in these people living alone at home.Undernutrition is a pathological condition resulting from insufficient nutritional intake in relation to the body's energy expenditure. It is a major public health issue in the management of older people with chronic pathologies (up to 50% of elderly people) (Volkert, 2019). It is associated with increased morbidity and mortality, risk of loss of autonomy, falls, infections and emergency hospitalizations (Norman, 2021). In France, 400 000 elderly people at home suffer from undernutrition, so it is important to better understand the behaviors related to undernutrition. The use of digital biomarkers for the early detection of functional or cognitive decline is receiving increasing attention (Piau, 2020). For example, sensor-derived mobility indicators have been studied to predict an upcoming fall in older people (Piau, 2015). Currently, the assessment of an individual's eating behavior relies mainly on self-report measures and clinical tests. Although this methodology is necessary, it can be improved as it is limited by recall bias and by brief and mostly episodic assessments. Continuous real-time monitoring by a low-cost ambient sensors network can provide a more sensitive, objective and environmentally valid method to:

-Detect sub-clinical alteration in nutrition during chronic disease, prior to the onset of symptoms (allowing for targeted, personalized and more effective medicine (rather than one-size-fits-all medicine);

-Make a less biased assessment of treatment efficacy and side effects in a clinical trial after treatment modification;

-Remotely monitor the dynamics of recovery after hospitalization or surgery.

2. RELATED WORKS

Previous studies have concretely linked the physiological and the biological state of an individual, which is already an indication for diagnosing undernutrition.

Busnel et al. (Busnel, 2018) propose to estimate the diagnostic accuracy of the nutritional status score, body mass index and weight loss documented from the Resident Assessment Instrument – Home Care (RAI-HC). A sample of 267 home care recipients aged 65 years and older was assessed using the RAI-HC and the Mini Nutritional assessment short form (MNA-SF). The result reveals that the diagnostic accuracy of the RAI-HC indicators was not sufficient for optimal screening for undernutrition in elderly home care recipients. Additional assessment with the MNA-SF is recommended to optimize early detection of individuals at risk for undernutrition.

Birkan et al. (Birkan, 2018) propose to investigate the reliability and validity of the Turkish version of the Simplified Nutritional Appetite Questionnaire (SNAQ) in geriatric outpatients. The results indicate that in terms of validity of the SNAQ, Cohen's kappa analysis showed fair to moderate agreement between the SNAQ and the MNA (κ=0.355, $p<0.001$). Female gender, illiteracy, functional dependence in activities of daily living was significantly associated with poor appetite. The SNAQ score was weakly correlated with the MNA-SF and MNA-LF scores (r=0.392 and r=0.380, respectively, $p<0.0001$ for both).

Gambi et al. (Gambi, 2020) propose an application to monitor the food intake actions of individuals during a meal. Eating actions are estimated from the analysis of depth images. In order to optimize and to increase the performance of algorithms, the idea is to automate the process that allows us to identify the different actions of taking meals.

One of the main findings of previous studies is that weight loss is a fundamental defect identified in the elderly.Other studies also suggest that albumin levels in laboratory tests may be related to undernutrition. Finally, the identification of biomarkers (Panagoulias, 2021) is also proving to be tools to accurately prognosticate many diseases, classify them by type and stage, and personalize medical care.

3. PROPOSED SYSTEM

The proposed research is part of the regional Inspire program (Barreto, 2020). Inspire is a research platform dedicated to gerontological research on biological and healthy ageing to identify biomarkers, determine biological age and work on all marks of ageing. Inspire involves 1000 participants. The two main projects are:

3.1 ICOPE Mobile Application

As shown in Figure 1, Integrated Care for Older People (ICOPE) (Tavassoli, 2021) is a mobile application launched by the World Health Organization (WHO) in 2019 for the integrated care of older people. This app measures intrinsic capacity which is the combination of different abilities (physical, mental and psychological) and functional ability. There are 6 domains of intrinsic capacity that can be measured: cognition, mobility, nutrition, mood, vision and hearing. In order to maintain the health of older people and to better identify risks before the frailty stage is reached, the application is used as a monitoring tool. It is based on 5 steps: 1-Screening for decline in intrinsic capacity, 2-Specialized assessment, 3-Creating a personal care plan, 4-Regular monitoring and 5-Career and community integration. To monitor undernutrition, patients answered two questions about:

-Weight loss: have you unintentionally lost more than 3 kg over the last three months?

-Appetite loss: have you experienced a loss of appetite?

By answering these two questions, we can identify markers related to nutrition. We can also establish a link between nutrition and reduced mobility.

In order to better collect biological markers, we use an annual in-depth assessment and questionnaires.

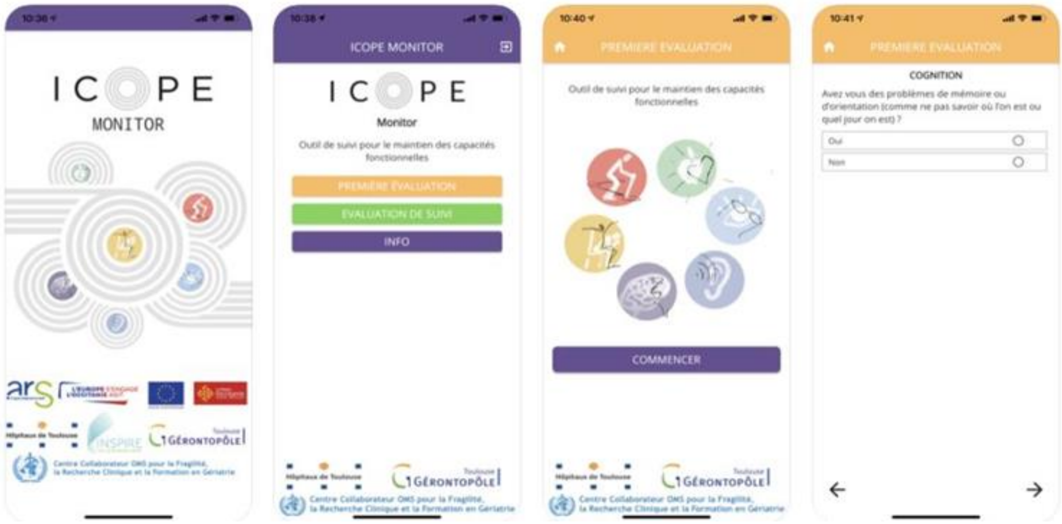

Figure 1. ICOPE Mobile application

3.2 CART France

Collaborative Aging Research using Technology (CART) Sensor Platform is an initiative developed by Oregon Center for Aging & Technology (ORCATECH)(Thomas, 2021) to study various physical and physiological parameters. CART France is a living lab project based on one hundred connected homes. ORCATECH's sensor platform proposes new ways to assess people with cognitive impairment. By using a huge amount of information about changes in health status, activity and functioning in a real-world setting to improve the ability to assess and provide personalized care. Differences between the French CART project and the U.S. CART project are the number of sensors used in both projects and the fact that the French CART project is based on the nutritional status of individuals. As shown in Figure 2, the sensors used in CART France are physical and physiological sensors.

The project aims to combine the CART French data with clinical data to evaluate the relevance of numerical data to represent and predict an individual's health status.

The inclusion criteria for participants are as follows:

1- Over 75 years old
2- Living alone at home without assistance
3- Being robust
4- Having a computer and an internet terminal

To retrieve the physical parameters, we used passive infrared (PIR) motion and contact sensors installed at 3 different locations in the individual's home:

-the 1st PIR motion sensor is a wall sensor; it is used to detect the presence of the person in the room;

-the 2nd PIR motion sensor is a line sensor; 4 of them are placed in the hallway to calculate the walking speed when the person moves between two rooms. This parameter has already been studied to predict falls (Piau, 2020);

-the 3rd sensor is a contact sensor installed on the front door to detect the entry and exit of the person from the house.

All these function sensors are wireless sensors that use ZigBee radio communication. In order to retrieve physiological parameters, other types of sensors such as an impedance scale and a connected smart watch are added. Detailed descriptions of the hub computer and sensors have been published previously (Beattie, 2020) (Thomas, 2020). Figure 2 shows the different sensors used in the CART France project.

Figure 2. Overview of devices in the CART France project

3.3 System architecture

The French CART project was launched in July 2022. In this section we will present one of the first installations using only PIR sensors and a contact sensor to monitor physical activities. The architecture of the position of the sensors in the house can be visualized in Figure 3.

Figure 3. Architecture for the house

The exact number of sensors required, which is set at 13 sensors:
- 4 line sensors.
- 8 wall sensors.
- 1 contact sensor.

Figure 4 shows the location of the sensors in the house. Since the installation is done, we were able to see by using the Raspberry Pi (RPi) control panel that all the sensors are working correctly as shown in Figure 5. These sensors are connected to a hub via a personal area network (PAN).

The most important process is to map the location of the sensors in the house. This means that we will find the specific data for each room, as shown in Figure 6.

Figure 4. Example of sensors installation in the house

MAC	Inventory Name	Type	Last Checkin	Last Event	State	Active	Battery
...D6A232B		Contact Sensor	53m	7m	Closed		
...A993496		Contact Sensor	14m	4h 8m	Closed		
...0C204E8		Presence Sensor	58m	4h 51m			
...0C1D5EC		Presence Sensor	1h 3m	4m			
...0C19E9D		Presence Sensor	1h 3m	5m			

Figure 5. Example of sensors assigned in the console

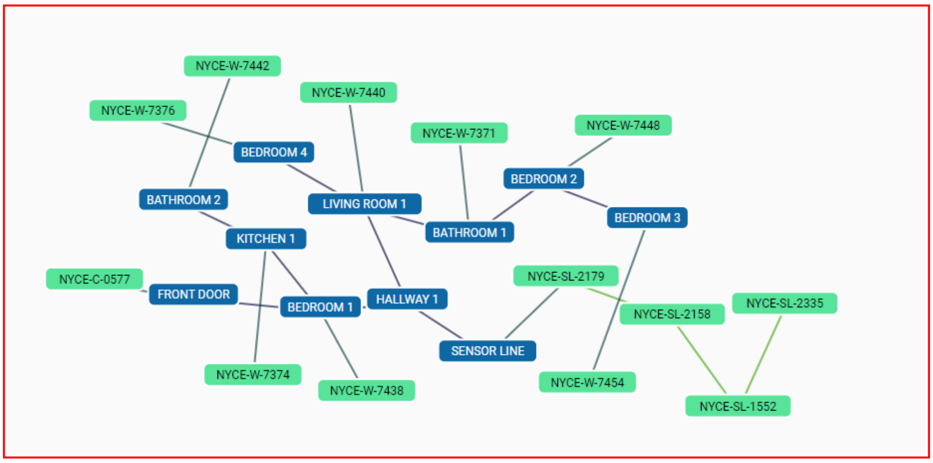

Figure 6. Location of sensors in the console

3.4 Data Collection

To date, we have collected 9 months of data. The objective of this data collection is to determine the life pattern corresponding to of this individual by correlating this data with the medical data from the weekly questionnaire and the ICOPE application. The collection and analysis of declarative data of people from the mobile application ICOPE are carried out in parallel to our study by the Hospital. They should make it possible to identify a change in the health state and appetite perception of the elderly.

The analysis described here is based on a naive approach that does not consider noise factors such as early triggering of sensors, transmission delay, or missing events, but it is sufficient to give a basic idea of their functionality. The data is stored in a database and includes all data set from all sensors. The resulting dataset was analyzed to find all walks in the walking line defined as a sequence of triggers of the 4 motion sensors (1,2,3,4 or 4,3,2,1) where the timestamps placed the sensors in a temporal order and where all sensors were triggered. Figure 7 shows the event logs in the database including homeid, stamp (date&time), areaid (room), itemid (sensors) and event (0: not in the room; 1: in the room).

homeid	study	stamp	itemid	areaid	event
2269	CART-FRANCI	17:08.1	27452	-1	0
2269	CART-FRANCI	17:12.4	27452	-1	1
2269	CART-FRANCI	17:15.9	27468	-1	1
2269	CART-FRANCI	17:21.1	23951	-1	1
2269	CART-FRANCI	17:21.1	23930	-1	1
2269	CART-FRANCI	21:05.4	23930	-1	0
2269	CART-FRANCI	21:05.6	23951	-1	0
2269	CART-FRANCI	21:16.9	27385	-1	0
2269	CART-FRANCI	35:13.8	27385	-1	0
2269	CART-FRANCI	35:50.1	27390	-1	0
2269	CART-FRANCI	36:44.9	24110	-1	0
2269	CART-FRANCI	37:13.8	27468	-1	0
2269	CART-FRANCI	37:41.2	27462	-1	0
2269	CART-FRANCI	38:05.0	27452	-1	0
2269	CART-FRANCI	38:35.8	27385	-1	1

Figure 7. Data Collection

If an areaid = -1, i.e. no sensors have been assigned to the room, as noted previously, to solve this problem, we need to build the sensors map (Figure 6). The first task is to preprocess the data by eliminating all insignificant areas.

	A	B	C
1	stamp	areaid	event
2	2022-07-27 10:34:03.357	29	1
3	2022-07-27 10:34:09.915	4	1
4	2022-07-27 10:34:14.157	29	0
5	2022-07-27 10:34:20.901	4	0
6	2022-07-27 10:35:56.845	4	1
7	2022-07-27 10:36:05.434	29	1

Figure 8. First Pre-Processing

Then, we only keep the information necessary for the analysis (stamp, areaid, events). On the other hand, in order to make correct and fast calculations, we need to convert time into Unix time, which allows us to filter events by area as shown in figure 9.

	A	B	C
1	stamp	areaid	event
2	1663658111	1	1
3	1663573521	1	1
4	1663573532	1	0
5	1663573544	1	1
6	1663073251	1	0

	A	B	C
24207	1659009059	4	0
24208	1659009054	4	1
24209	1659009045	4	0
24210	1659009040	4	1
24211	1659008207	4	0

Figure 9. Filtering of all events by areaid

Given the inter-individual variability in the physical activity intensity and duration, total energy expenditure can be estimated by multiplying resting energy expenditure by a factor reflecting the intensity of an individual's physical activity. This physical activity level factor (PAL) has been determined for many activities of daily living, including sedentary, occupational and sports activities (Westerterp, 2013).

$$PAL = \frac{TotalEnergyExpenditure}{BaselMetabolicRate}$$

The Basel Metabolism Rate (BMR) is obtained by the following basal metabolic rate formula:
-Men: BMR=88.362+ (13,397×weight in kg) + (4,799×height in cm) – (5,677×age in years)
-Women: BMR=447.593+ (9,247×weight in kg) + (3,098×height in cm) – (4,330×age in years)

Total energy expenditure=PAL×BMR

4. RESULTS AND DISCUSSION

Figure 10 shows an example of different events in each room of the house for 3 months of data. To better illustrate each of them, we represent each room by a histogram as shown in Figure 11. Each room contains events from which we can well distinguish the different activities of daily life, thus identifying a life pattern of that person. Finally, this will give us the ability to identify digital biomarkers.

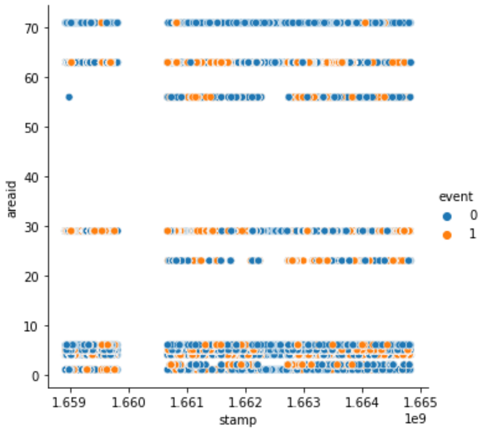

Figure 10. All the events that occurred in the house for 3 months

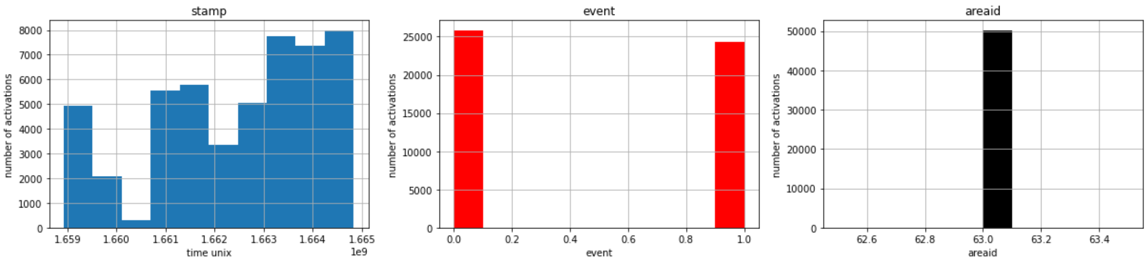

Figure 11. All events that occurred in area 63 for 3 months

We can also conclude that the use of PIR sensors not only detects the various activities of the person but it can also show the lifestyle which we can associate to other parameters to develop a very specific model for that person. It can also be used to calculate caloric expenditure. The data to calculate the BMR are for an individual with the following characteristics: age 77 years, sex: male, height 165 cm, weight 60 kg and work: writer.

$$BMR_{Men} = 88.362 + (13.397\times60) + (4.7988\times165) - (5{,}677 \times 77) = 1{,}246.855 \text{ cal}$$

Based on the lifestyle of the person in the house, we can classify this person in the PAL category between [1.4 and 1.69], which means he has a low-activity lifestyle.

$$Total\ Energy\ Expenditure = 1.4\times1\ 246.855\ cal = 1745.597 \text{ Cal.}$$

From the results of the weekly questionnaire, we can theoretically identify the lifestyle of the participants and validate this study by checking the activities records. The combination of the two studies (numerical and clinical) will explain and validate the results. However, the results of our analysis are approximately correct in the case where we measure the amount of daily energy spent in the home only. If we wish to calculate total daily energy expenditure, we must include other types of sensors, such as a Smartwatch, to monitor the total amount of activity inside and outside the home.

5. CONCLUSION

In this paper, we have presented a new system based on a regional research projects at the University Hospital Center in Toulouse-France. The CART initiative followed a principled design process to develop a platform capable of monitoring different fields of health and well-being. The data collected is typically used to explain, influence and/or predict health-related outcomes. In the case of CART France, the data collected must be used to identify nutrition-related behavior. To do this, we collect all the information related to the person's life habits such as the time, occurrences and duration of presence in each room, in our case the kitchen, as well as the use of household appliances such as the refrigerator. The use of digital biomarkers to detect subtle behavioral variations (undernutrition) prior to a clinical event is important to better understand individuals' adherence to recommendations. Actimetric measurements could be considered as a ‘partial’ parameter to be integrated with others, closer to physiological conditions. To this end, the combined use of clinical data (biannual nutrition assessment) and digital data (measurement of physical and physiological parameters, such as weight) will allow better diagnosis and prevention of situations at risk of undernutrition.

REFERENCES

Barreto De Souto, P., Guyonnet, S., Ader, I., Andrieu, S., Casteilla, L., Davezac, N., ... & Vellas, B. (2020). The Inspire Research Initiative: A Program for Geroscience and Healthy Aging Research going from Animal Models to Humans and the Healthcare System.

Beattie, Z., Miller, L. M., Almirola, C., Au-Yeung, W. T. M., Bernard, H., Cosgrove, K. E., ... & Kaye, J. (2020). The collaborative aging research using technology initiative: An open, sharable, technology-agnostic platform for the research community. *Digital Biomarkers*, *4*(1), 100-118.

Busnel, C., & Ludwig, C. (2018). Screening for undernutrition among older adults receiving home care: an estimation of the diagnostic accuracy of indicators available in the Resident Assessment Instrument-Home Care adapted for Switzerland. *Recherche en soins infirmiers*, *132*(1), 54-63.

Gambi, E., Ricciuti, M., & De Santis, A. (2020). Food intake actions detection: An improved algorithm toward real-time analysis. *Journal of Imaging*, *6*(3), 12.

İlhan, B., Bahat, G., Oren, M. M., Kilic, C., Durmazoglu, S., & Karan, M. A. (2018). Reliability and validity of Turkish version of the Simplified Nutritional Appetite Questionnaire (SNAQ). *The journal of nutrition, health & aging*, *22*, 1039-1044.

Norman, K., Haß, U., & Pirlich, M. (2021). Malnutrition in older adults—recent advances and remaining challenges. *Nutrients*, *13*(8), 2764.

Panagoulias, D. P., Sotiropoulos, D. N., & Tsihrintzis, G. A. (2021, November). Biomarker-based deep learning for personalized nutrition. In *2021 IEEE 33rd International Conference on Tools with Artificial Intelligence (ICTAI)* (pp. 306-313). IEEE.

Piau, A., Charlon, Y., Campo, E., Vellas, B., & Nourhashemi, F. (2015). A smart insole to promote healthy aging for frail elderly individuals: specifications, design, and preliminary results. *JMIR rehabilitation and assistive technologies*, *2*(1), e4084.

Piau, A., Mattek, N., Crissey, R., Beattie, Z., Dodge, H., & Kaye, J. (2020). When will my patient fall? Sensor-based in-home walking speed identifies future falls in older adults. *The Journals of Gerontology: Series A*, *75*(5), 968-973.

Piau, A., Wild, K., Mattek, N., & Kaye, J. (2019). Current state of digital biomarker technologies for real-life, home-based monitoring of cognitive function for mild cognitive impairment to mild Alzheimer disease and implications for clinical care: systematic review. *Journal of medical Internet research*, *21*(8), e12785.

Tavassoli, N., Piau, A., Berbon, C., De Kerimel, J., Lafont, C., De Souto Barreto, P., ... & Vellas, B. (2021). Framework Implementation of the INSPIRE ICOPE-CARE program in collaboration with the World Health Organization (WHO) in the Occitania region. *The Journal of frailty & aging*, *10*, 103-109.

Thomas, N. W. D., Beattie, Z., Marcoe, J., Wright, K., Sharma, N., Mattek, N., ... & Kaye, J. (2020). An ecologically valid, longitudinal, and unbiased assessment of treatment efficacy in Alzheimer disease (the EVALUATE-AD Trial): proof-of-concept study. *JMIR Research Protocols*, *9*(5), e17603.

Thomas, N. W., Beattie, Z., Riley, T., Hofer, S., & Kaye, J. (2021). Home-based assessment of cognition and health measures: The collaborative aging research using technology (CART) initiative and international collaborations. *IEEE Instrumentation & Measurement Magazine*, *24*(6), 68-78.

Volkert, D., Beck, A. M., Cederholm, T., Cereda, E., Cruz-Jentoft, A., Goisser, S., ... & Wirth, R. (2019). Management of malnutrition in older patients—current approaches, evidence and open questions. *Journal of clinical medicine*, *8*(7), 974.

Westerterp, K. R. (2013). Physical activity and physical activity induced energy expenditure in humans: measurement, determinants, and effects. *Frontiers in physiology*, *4*, 90.