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Detection of social isolation based on meal-taking activity and mobility of elderly people living alone

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Abstract

Social isolation is likely to be one of the most affected health outcomes for the elderly due to the COVID-19 pandemic especially for seniors living alone at home. Therefore, we seek to identify it based on detecting changes in the elderly such as malnutrition and lack of mobility. In this article we present our sensor monitoring system that was implemented for 15 days in the home of a 26-year-old student living alone as a first step to later deploy in the home of elderly people. Then, we present our results based on the data collected by sensors during the experiment. Our study showed the feasibility of automatic identification of the (1) meal-taking activity (shopping, cooking, eating and washing dishes) and (2) mobility (inside the home and the act of going out). These results are an intermediate step in assessing the social isolation status of the elderly based on these ADLs.

Keywords: *Social isolation, Meal-taking activity, Mobility, monitoring systems.*

I. INTRODUCTION

According to the UN (United Nations), people aged 65 and over will represent 16% of the world's population in 2050 [1]. Securing and supporting this population is therefore a growing concern, as advancing age encourages the appearance of risks of physical, cognitive and relational degradation. Indeed, an American report from the National Academies of Science, Engineering, and Medicine (NASEM), carried out before the COVID epidemic in 2020, points out that 24% of adults aged 65 and over living in the community in the United States (representing approximately 7.7 million people) were socially isolated [2]. With the COVID-19 pandemic, this number is increasing dramatically due to the stay-at-home orders, social distancing and banning visits for nursing home residents. While social isolation and loneliness are closely related, they do not mean the same thing. According to UK's National Institute for Health Research, isolation is a lack of social contact or support, whereas loneliness is the feeling of being alone and isolated (it

is possible to feel lonely in a room full of people) [3]. The social isolation of the elderly is a risk factor for malnutrition [4], reduced mobility [5] and physical fragility [6]. Moreover, the desire to live independently at home increases significantly among the elderly due to attachment to their home and the cost of care in retirement homes. With the growing advances in technological monitoring system, elderly people can stay in their homes and their family feels safe and secure about them. Therefore, we focused on two activities of daily living (ADLs) that seem relevant for a predicting social isolation by detecting behavioral drift: (1) the meal-taking activity (shopping, cooking, eating and washing dishes) and (2) mobility (inside home and the act of going out).

The automatic classification of these ADLs can be challenged since every person has his/her own rhythm to do it especially the meal-taking activity process.

To meet these challenges, we are working on a monitoring system based on miniaturized sensors distributed in the person's living environment to detect changes in behavior (whether sudden or slow over time), and then to propose an intervention in line with the behavior, the person's abilities and his/her living context. For example, the elderly may begin to skip the dinner (compared to other days), the system notifies the caregivers/family of the situation and issues reminders to the elderly at the usual lunchtime to motivate them to eat.

Our work focuses on the following points: (i) Continuous and longitudinal monitoring through the deployment of low-cost, discrete, non-intrusive and miniaturized sensors in the individual's home; (ii) Automatic identification of processes related to home mobility and meal-taking. A learning phase will be carried out to model the behavior pattern of individuals; (iii) Establishing the link between these 2 activities and social isolation, a phenomenon that has been reinforced with the global COVID-19 crisis. This problem has been highlighted especially among the elderly who are living alone.

Our contributions can be summarized as follows:

-We introduce our sensor monitoring system and its deployment in a home of a person living alone. We show the feasibility of the system to monitor the targeted ADLs.

- We define the targeted ADLs and our approach for their automatic identification.
- We present the results of the sensor data analysis over 15 days for a test individual.

II. BACKGROUND AND RELATED WORK

Automatic classification of ADL is a crucial part of ambient assisted living (AAL) technologies. It enables to monitor the daily life of the elderly and to detect any change in their behavior to encourage them to live independently and safe in their home. Many studies in AAL focus on different ADLs, such as bathing, grooming, mobility inside and outside the home, eating... In this study, we focus on systems related to two main ADLs that we assume they could have connection with social isolation: the process of taking meals (food shopping, cooking, eating and dishwashing) and mobility (inside home and the act of going out).

Huynh et al. [7] propose a system composed of two types of non-intrusive sensors, a passive infrared (PIR) sensor in each room and a reed switch to detect the main door opening and closing. After a real deployment of the system in 50 flats of seniors living alone and the completion of a mental health and loneliness survey, this study demonstrates that the system can detect the outing behavior of the elderly people living alone and identify potential candidates with severe loneliness and depression problems based on the ratio of time spent inside and outside the flat.

Lussier et al. [8] propose a system composed of three types of sensors: passive infrared (PIR) sensors, magnetic contact sensors, and smart electric switches based on the request of Integrated Health and Social Services Centers (IHSSC) home care division of Montreal. The objective of the system is to improve the support provided to home care recipients who are at risk of self-neglect. Results from 3 older adults show that the system can collect data on the home care recipients' life habits, such as daily patterns related to eating, sleeping, personal care, inactivity and going outside.

Cippitelli et al. [9] present a solution to monitor the food and drink intake actions of elderly. It uses a depth and RGB camera placed on the ceiling. The depth information is applied to track the person's movements and the RGB stream is used to recognize specific elements located on the table during eating-related activities, such as glasses. The fusion of these processed data leads to the identification of specific intake behaviors. Experimental tests show the ability of the system to recognize intake actions.

While all these studies use different types of sensors and focus on monitoring of some ADLs, we consider it as an intermediate step to assess the social isolation status of the elderly. In addition, user acceptance of the elderly monitoring system is a compromise between user needs and perception, especially with respect to privacy. A study carried out to get older people's

perspectives regarding the use of sensors [10] indicates that the older persons surveyed evaluated sensor monitoring positively because it gives them a sense of safety as an important premise for independent living. In addition, sensors that record their movements at home without cameras or sound recordings are not considered as an invasion of their privacy. Therefore, this article proposes unobtrusive and passive sensor system that can assess the social isolation status of elderly based on the process of taking meals and mobility.

III. MOBILITY AND MEAL-TAKING ACTIVITY

A. Mobility

Mobility is defined as the ability to move freely or be easily moved. Mobility is very important to maintain self-care, independent and autonomous lifestyle of the elderly. Indeed, regular mobility and activity, even mild physical activity such as walking, enable to improve mental and cardiovascular health, control weight, maintain healthy bones and muscles, reduce the risk of falling and increase social interaction [11].

An American study on Time-Location Patterns realized in six cities indicates that adults aged 65 and over, spent 78% of their time at home. This result is understandable as older people are generally retired, have limited social contacts and therefore prefer to spend most of their time at home [12]. Thus, we will focus in our study on the monitoring of activities inside the home and the act of going out.

B. The meal-taking activity

Recognizing the activity of eating is very important for monitoring the health of the elderly. In fact, good nutrition has a huge impact on physical health, memory and mental function. And with age, eating well can boost immunity, fight illness-causing toxins, keep weight in check, and reduce the risk of heart disease, stroke, high blood pressure, type-2 diabetes, bone loss, Alzheimer's disease and cancer [13]. Unfortunately, malnutrition exists among older people and represents an issue that is not yet well investigated. According to the National Health Service of United Kingdom, among the 12.2 million older people, around one million over 65 are malnourished or at risk of malnutrition, most of them (93%) living at home, so their malnutrition goes often unnoticed [14]. Identifying all eating-related activities is the best way to analyze them correctly. The meal-taking activity consists of 4 ADLs: food shopping, cooking, eating and dishwashing.

Food shopping: Food shopping is the activity whereby a person goes to the market to buy different ingredients to cook or to buy ready-made meals. For the elderly, food shopping is not a simple activity, but it is considered as an important social event. In fact, for some older people living alone, this is the only opportunity

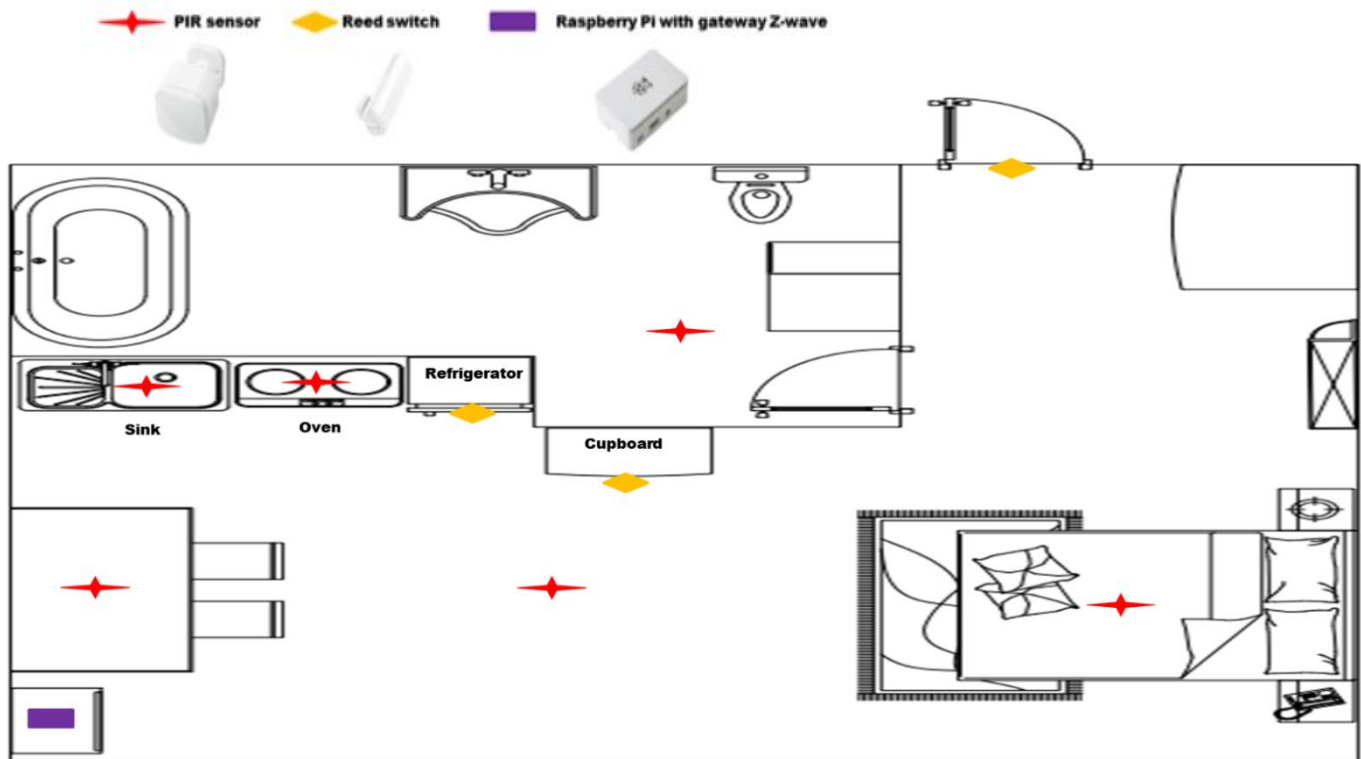


Figure 2. Distribution of sensors at home

Trisensor from Aeotec also includes temperature, brightness and humidity.

Each room in the home is covered by one PIR sensor with the addition of three PIR sensors on top of the sink, oven and dining table. The reed switch is installed in the outside door, refrigerator and cupboard. The power meter is equipped with most used electrical devices depending on the use of the person such as TV, toaster, microwave... In addition, a pack of Raspberry Pi with Z-wave gateway collects data from the sensor through Z-wave protocol. Since the sensors will be easily installed in specific locations, as mentioned above, the system will be indifferent to the type of house where it will be deployed. Figure 2 shows an example of a home installation. It represents the distribution of devices in a home young person. The temperature, luminosity, humidity and power meter sensors were not depicted in Figure 2 because we only use in this work data obtained from the doors and motion sensors.

V. DATA COLLECTION

The data used in this study was collected from the home of a young man. He is a 26-year-old student living alone and without any health disorders. The purpose of this experimentation is to validate the technical installation and the choice of sensors and to collect real data in the participant's

home to develop and test our algorithm. No specific scenario

was performed by the participant. The aim of this data collection is to know how these ADLs are realized by the person in real life in his home and to detect any problem when there is a change in his routine. The next step will be to deploy the system in the homes of elderly people living alone. The 9-sensor dataset contains 29,388 events recorded over 15 days for one month ((December 2020). The data is recorded in real time in a database of the DomoticZ software in the Raspberry Pi.

The PIR sensors detect movement in the motion area and the reed switch detects the opening or closing of the door. The PIR sensor works by sending a '1' signal when detecting a movement and '0' after 1 second of movement detection, with a refractory period of 5 seconds after movement detection. The reed switch sends a '1' signal when detecting the opening of the door and '0' when it detects the closing of the door. The Raspberry Pi and the Z-wave gateway uses DomoticZ, a home automation software, to collect and store data sent by the sensors through the wireless mesh network using the Z-wave wireless module of each sensor. The event logs in the database include date, time, sensor type and its status. The identification of the targeted ADLs will depend only on the data collected by these sensors.

VI. ADLS IDENTIFICATION

A. Home status



Figure 3. Number of events detected by sensors

VII. RESULTS

Figure 3 shows the number of sensor activations during this test period. The periods of 8 to 9am, 12 to 2pm and 7 to 10pm contain the greatest number of events detected by the sensors, especially the detection of the person around the oven, and this is comprehensive because it seems that this time corresponds to meal preparations.

In addition, we can see that between 10pm to 8am, the greatest number of sensor activations is the PIR bed, and this shows that the person is in his/her bed awake then asleep (between 1

to 8am shows that few events are detected by the sensors and this point out that the person is sleeping and does few movements in bed).

These results depend a lot on the daily rhythm of the elderly that is why the system should be personalized.

Even so, a person's daily pattern can vary from day to day, as shown in Figure 4, especially on weekends and weekdays.

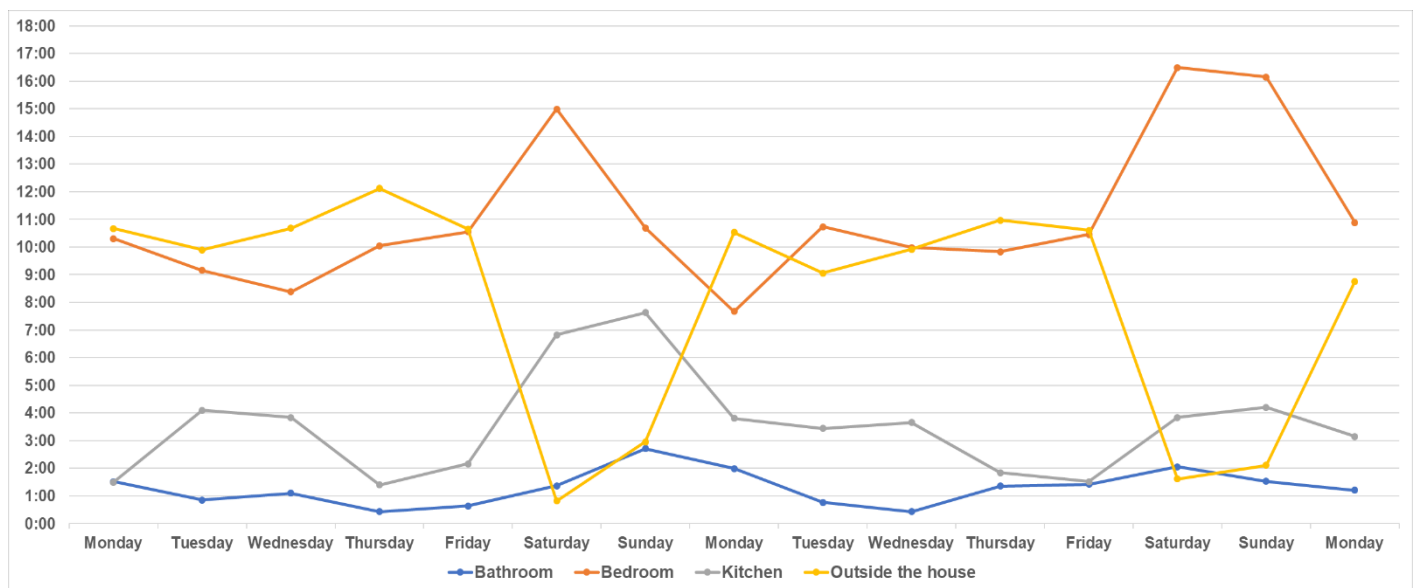


Figure 4. Distribution of time spent inside and outside the home

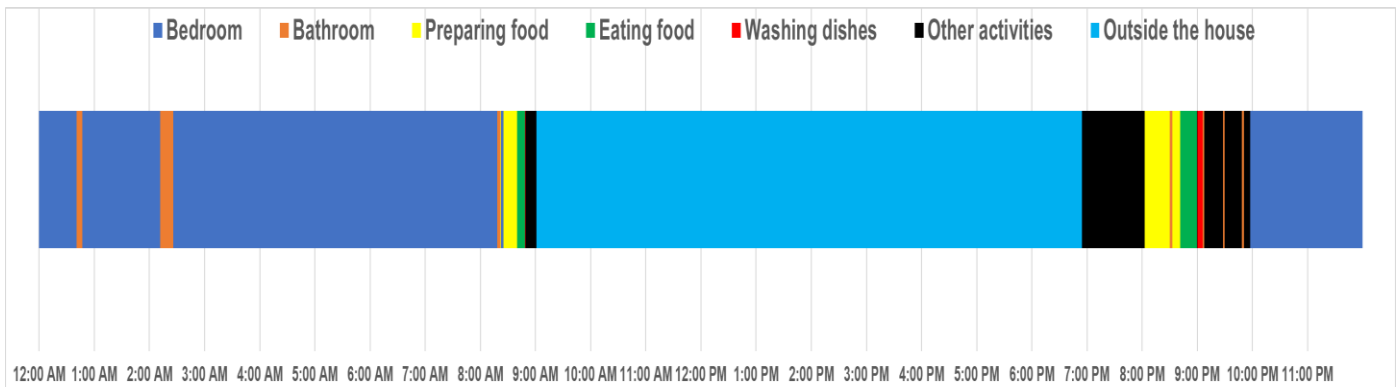


Figure 5. Distribution of time spent inside and outside the home

In our case, there is a big difference in the time spent outside the home respectively from 8h45m on the last Monday to 1h36m on the second Saturday. This difference is logic because the person being followed is a student and he attends his studies during the week. In addition, there is a pattern of duration of time outside the house. In fact, the average time outside the house on the weekday is 10h21m with a maximum of 12h7m and a minimum of 8h45m.

Regarding meal-taking activity, the person spent an average of about 3h31m in the kitchen with a significant increase on weekends (the person spent 7h37min in the kitchen on the first Sunday, and this difference makes sense given that the person eats their lunch outside the home on weekdays and weekends can be an opportunity to prepare meals with longer preparation, uneasy to prepare during weekdays). Overall, the person's daily presence in the kitchen reflects the regularity of the meal-taking activity.

Regarding hygiene, the person spent an average of about 1h17m in the bathroom with a maximum of about 2h42m and a minimum of 0h25m. Therefore, the duration of this activity was distributed relatively evenly over the entire test period.

Figure 5 shows an example of activities detected during a day. It represents 7 activities detected by the sensors (other activities corresponding to those different from the 6 others like playing the piano, cleaning the table after the meal, etc.). It shows the targeted ADLs such as preparing food, eating it, washing the dishes, going outside the home. In fact, he spent, 15m29s and 36m9s in preparing food then 8m26s and 17m43s eating it for breakfast and for dinner, respectively. And he washes the dishes for 5m21s in the evening.

The extraction of this information allows us to have a good insight on the person's daily pattern and thus to detect changes in their behavior (whether sudden or slow over time). Our system will work, using different conditions related to meal-taking activity and mobility, at two level of data analysis. For

example, in the first level which is the real time level and based on the model built during the learning phase (one or two weeks/week ends), the system will trigger the loudspeaker to motivate the elderly person to eat if he/she makes an unusual delay of this activity (nutrition is very important for the health of the elderly that is why we need to motivate him/her in real time). And if he/she does not respond to our motivation, we inform the caregiver of this state by sending an alert in the web application. And for the second level, which is the long-term analysis, the data model evolution can reveal a degradation of the time of eating activity. We can conclude from this degradation that he starts to eat less than usual. An alert will be sent to the caregiver and an intervention from him is so necessary.

VIII. CONCLUSION

In our study, we presented a sensor-based monitoring system composed of PIRs and a reed switch to monitor the activity pattern of people at home.

Analysis of the data collected during 15 days of follow-up for a person living alone allowed us to detect the meal-taking activity (shopping, cooking, eating and washing dishes), mobility (inside home and the act of going out) and the difference of daily pattern between the weekend and weekday.

The system aims to automatically identify the meal-taking activity and mobility to identify social isolation of the elderly. It will respond to each case accordingly to the level of change in their behavior by motivating them to eat and move around and triggering an alert in case of a problem.

In a next step, we will use AI for automatic identification of ADLs, perform tests in the homes of elderly people living alone and detect those cases with abnormal patterns likely to be linked to social isolation problem.

REFERENCES

- [1] <https://www.un.org/en/global-issues/ageing#:~:text=According%20to%20data%20from%20World,be%20aged%2065%20or%20over.>
- [2] National Academies of Sciences E, and Medicine. The National Academies Press; Washington, D.C.: 2020. Social Isolation and Loneliness in Older Adults: Opportunities for the Health Care System.
- [3] Interventions for loneliness and social isolation National Institute for Health Research. The University of York Centre for Reviews and Dissemination. 2014.
- [4] Boulos C, Salameh P, Barberger-Gateau P. Social isolation and risk for malnutrition among older people. *Geriatr Gerontol Int.* 2017 Feb;17(2):286-294. doi: 10.1111/ggi.12711. Epub 2016 Jan 21. PMID: 26790629.
- [5] Schrepft, S., Jackowska, M., Hamer, M. et al. Associations between social isolation, loneliness, and objective physical activity in older men and women. *BMC Public Health* 19, 74 (2019). <https://doi.org/10.1186/s12889-019-6424-y>
- [6] Gale CR, Westbury L, Cooper C. Social isolation and loneliness as risk factors for the progression of frailty: the English Longitudinal Study of Ageing. *Age Ageing.* 2018 May 1;47(3):392-397. doi: 10.1093/ageing/afx188. PMID: 29309502; PMCID: PMC5920346.
- [7] Huynh, Sinh; TAN, Hwee-Pink; and LEE, Youngki. Towards unobtrusive mental well-being monitoring for independent-living elderly. (2017). WPA '17: Proceedings of the 4th International on Workshop on Physical Analytics, Niagara Falls, June 19. 1-6. Research Collection School of Information Systems
- [8] M. Lussier, M. Couture, M. Moreau, C. Laliberté, S. Giroux, H. Pigot, S. Gaboury, K. Bouchard, P. Belchior, C. Bottari, G. Paré, C. Consel, N. Bier (2020). Integrating an Ambient Assisted Living monitoring system into clinical decision-making in home care: An embedded case study. *Gerontechnology*, 19(1), 77-92 <https://doi.org/10.4017/gt.2020.19.1.008.00>
- [9] E. Cippitelli, S. Gasparrini, E. Gambi and S. Spinsante, "Unobtrusive intake actions monitoring through RGB and depth information fusion," 2016 IEEE 12th International Conference on Intelligent Computer Communication and Processing (ICCP), Cluj-Napoca, Romania, 2016, pp. 19-26, doi: 10.1109/ICCP.2016.7737116.
- [10] Margriet Pol, MSc, Fenna van Nes, PhD, Margo van Hartingsveldt, MSc, Bianca Buurman, RN, PhD, Sophia de Rooij, MD, PhD, Ben Kröse, PhD, Older People's Perspectives Regarding the Use of Sensor Monitoring in Their Home, *The Gerontologist*, Volume 56, Issue 3, June 2016, pp. 485-493, <https://doi.org/10.1093/geront/gnu104>
- [11] <https://www.sunshineretirementliving.com/sunshine-stories/7-remarkable-reasons-encourage-promote-senior-mobility/>
- [12] Spalt EW, Curl CL, Allen RW, Cohen M, Adar SD, Stukovsky KH, Avol E, Castro-Diehl C, Nunn C, Mancera-Cuevas K, Kaufman JD. Time-location patterns of a diverse population of older adults: The Multi-Ethnic Study of Atherosclerosis and Air Pollution (MESA Air). *J Expo Sci Environ Epidemiol.* 2016 Jun;26(4):349-55. doi: 10.1038/jes.2015.29. Epub 2015 Apr 29. Erratum in: *J Expo Sci Environ Epidemiol.* 2016 Jun;26(4):436. PMID: 25921083; PMCID: PMC4641054.
- [13] <https://www.helpguide.org/articles/healthy-eating/eating-well-as-you-age.htm>
- [14] <https://digital.nhs.uk/data-and-information/find-data-and-publications/supplementary-information/2018-supplementary-information-files/hospital-admissions-for-scurvy-rickets-and-malnutrition>
- [15] Dagmar Lesakova, Seniors and Their Food Shopping Behavior: An Empirical Analysis, *Procedia - Social and Behavioral Sciences*, Volume 220, 2016, Pages 243-250, ISSN 1877-0428, <https://doi.org/10.1016/j.sbspro.2016.05.496>.
- [16] Healy AE. Eating and ageing: A comparison over time of Italy, Ireland, the United Kingdom and France. *International Journal of Comparative Sociology.* 2014;55(5):379-403. doi:10.1177/0020715214561132
- [17] Sulmont-Rossé C. (2020) Eating in the Elderly. In: Meiselman H. (eds) *Handbook of Eating and Drinking.* Springer, Cham. https://doi.org/10.1007/978-3-030-14504-0_37
- [18] Guyonnet S, Rolland Y. Screening for Malnutrition in Older People. *Clin Geriatr Med.* 2015 Aug;31(3):429-37. doi: 10.1016/j.cger.2015.04.009. Epub 2015 May 13. PMID: 26195101.
- [19] LaMonte MJ, Buchner DM, Rillamas-Sun E, Di C, Evenson KR, Belletiere J, Lewis CE, Lee IM, Tinker LF, Seguin R, Zaslovsy O, Eaton CB, Stefanick ML, LaCroix AZ. Accelerometer-Measured Physical Activity and Mortality in Women Aged 63 to 99. *J Am Geriatr Soc.* 2018 May;66(5):886-894. doi: 10.1111/jgs.15201. Epub 2017 Nov 16. PMID: 29143320; PMCID: PMC5955801.
- [20] <https://www.insee.fr/fr/statistiques/2118039?sommaire=2118074>