SEARCHING FOR FALLS TRAJECTORIES OF THE ELDERLY

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ABSTRACT

The fall of the elderly is of great interest in geriatric. It can be linked to other diseases that make the elderly person frailer. Using Group Based Trajectory Modeling (GBTM) and K-means for longitudinal data (KML), we were able to find the trajectories that characterize our study population. Our participants were initially divided in two, randomly. We explored the trajectories that characterize the control group and the intervention group. We found five with the KML and four with the GBTM in the total study population and in each group. One of the groups is the intervention group and the other is the control group. The trajectories obtained in the intervention group testify to the impact of home-based interventions. The effectiveness of post-fall prevention is observed in both groups. However, the size of the sample and the limited number of falls recorded are a hindrance to the generalization of the results of the study.

KEYWORDS:

Geriatrics, Fall, Elderly, Mathematical Modeling, Longitudinal Data

1. INTRODUCTION

Just as children and adolescents have pediatrics as a medical specialty, the elderly have geriatrics. Geriatrics has become an increasingly popular field and has been a specialty in France since 2004 (Sénat, 2023). Regarding the study of aging, gerontology is the term used, which draws upon several fields including medicine, sociology, psychology, anthropology, economics, and many others (Bimou, 2019). This makes gerontology a rich field for collecting data that can help better understand patients and improve the quality of life for older adults. The objective is not to prevent aging, but to ensure that it goes well, which is referred to as "aging well" (US Preventive Services Task Force, 2018).

According to the World Health Organization (WHO), in 2019 out of the world's population of 7.7 billion people, more than 1 billion (13.2%) were 60 years old or older, compared to 382 million in 1980. This number is expected to increase to 2.1 billion by 2050 (WHO, 2023).

The narrowing of the birth rate in France and life expectancy, which is currently 85 years for women and 79 years for men as of 2021, has led to a considerable increase in the number of people over 65 years old (Insee, 2023). According to the National Institute of Statistics and Economic Studies (Insee), from 2016 to 2021, the number of inhabitants aged 65 or over increased by 1,379,699 in metropolitan France. In the group aged 75 or over, this number increased by 296,933; this strong increase will continue until 2035. This number will increase by 10 million by 2060, and one third of the population will be over 60 years old (Insee, 2023).

Studies aimed at finding ways to delay and improve aging are underway, with the goal of identifying ways to slow down the often irreversible consequences of aging (Park, 2018). Data collected from a Comprehensive Geriatric Assessment (CGA) on a cohort of people aged 75 and over are longitudinal and will help identify fall trajectories using statistical methods that have already produced promising results in this field. This statistical analysis will provide the physician with clues to improve their care (Tchalla et al., 2014).

2. GENERALITIES, MATERIALS, AND TOOLS

A fall is a complex event. To fully understand it, a comprehensive assessment of the older adult is necessary. The more information we have about them, the better it is. In this study, the protocol used allowed to collect as much information as possible from the participants.

2.1 Fall

A fall occurs when a person involuntarily ends up on the ground or at a lower level than their starting position (Moylan & Binder, 2007). Events caused by loss of consciousness, a violent push, stroke, or epileptic seizure are excluded. Falls can lead to disability, fractures, and even psychological trauma, making fall prevention a public health priority (SPF, 2023). The objective is to combat the rapid deterioration of the health of the population, especially the most affected: older people. To do this, it is essential to identify early warning signs of a first fall (Park, 2018). A first fall can lead to a reduction in physical activity, which is beneficial for maintaining the health of older adults, due to the fear of falling again (Mignardot et al., 2014). A fall may not be serious and may be repeated in some people, and this is referred to as "repeated falls" in geriatrics if a person falls at least twice in 12 months (WHO, 2023).

2.2 Comprehensive Geriatric Assessment (CGA)

The Comprehensive Geriatric Assessment (CGA) is a multidimensional and standardized approach that improves practices in the care of older people through a health assessment (Bimou, 2019).

2.3 Study Framework

Over a period of two years, the Unité de Prévention, de Suivi et d'Analyse du Vieillissement (UPSAV) collected data on 440 participants through the clinical research protocol GEROPASS during home visits conducted by a geriatrician and a nurse. The data from the Comprehensive Geriatric Assessment (CGA) were collected at the beginning of the study, which is the initial visit or V0 (it allows to take a snapshot of the participant's health at entry and to construct his/her Personalized Care Plan (PPS)), during the two visits that followed V1 (at 6 months) and V3 (at 12 months) but also at the end of 24 months, which is the visit V3 (it allowed to take a snapshot of the participant's health upon exiting the study).

Throughout the study, the intervention group participants had the four planned visits during the two years of the study. However, those in the control group only had the V0 and V3 visits (Figure 1). They didn't have the Personalized Care Plan (PPS).

The participants are men and women aged 75 and over.

To be included, participants must:

- provide written informed consent from the participant or their legal representative,
- not be participating in a clinical trial that modifies the patient's management,
- not have progressive pathologies that could affect short-term prognosis,
- not be in a Long-Term Care Unit (USLD) or in a Nursing Home for Dependent Elderly People (EHPAD),
- have a Mini Mental State Examination (MMSE) score of 10 or higher,
- be covered by social security at 100%.

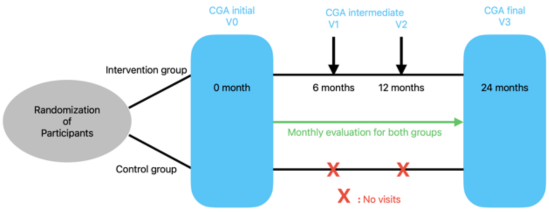

Figure 1. Study design

2.4 Database Formatting

The data is collected through home visits conducted by the Aging Prevention, Monitoring and Analysis Unit (UPSAV) and telephone calls made by the Clinical Research and Innovation Unit (URCI). In order to have a database with the necessary information, we joined the call database with the V0 visit database using Excel. This resulted in a database of 167 individuals, of which 79 are controls and 88 are interventions.

2.5 Descriptive Analysis

Table 1 shows the distribution of the 167 participants and their characteristics according to group. They have an average age of 83 years and are predominantly female (118 women and 49 men).

Table 1. Descriptive analysis of the study population by group at V0

		Over all	Both study groups		
Variables	N	N=167[1]	Intervention group, N= 88[1]	Control group, N=79[1]	p_{value}[2]
AGE	167	83.0 (80.0, 88.0)	83.0 (80.0, 89.0)	83.0 (80.0, 87.5)	0.98
Sex	167				0.34
Female		118 (71%)	65 (74%)	53 (67%)	
FALL HISTORY	167				**0.046**
No		42 (25%)	18 (20%)	24 (30%)	
Yes		107 (64%)	56 (64%)	51 (65%)	
Not specified		18 (11%)	14 (16%)	4 (5%)	
BMI	167				**0.022**
$\geq$ 21kg/m^2		147 (88%)	72 (82%)	75 (95%)	
<21 kg/m^2		10 (6.0%)	9 (10%)	1 (1.3%)	
<18 kg/m^2		10 (6.0%)	7 (8.0%)	3 (3.8%)	
OUTDOOR WALK	167				**<0.001**
No		10 (6.0%)	10 (11%)	0 (0%)	
Yes		71 (43%)	71 (81%)	0 (0%)	
Not specified		86 (51%)	7 (8.0%)	79 (100%)	
DAILY MEDICATION $\geq$ 4	167				0.35
Yes		124 (74%)	68 (77%)	56 (71%)	

1 Median (Interquartile Range) or Proportion (%)
2 Wilcoxon rank sum test; Pearson's Chi-squared test; Fisher's exact test

We see this average age in both study arms. We can note that the control group participants are younger than those in the intervention group. They consist of fewer women (53 versus 65) and fewer people with a history of falls (51 versus 56). A history of falls is a fall that occurred before the start of the study.

Study participants have a predominant FALL HISTORY. They represent more than 60% in each study group.

Most participants (147 or 88%) have a Body mass index (BMI) that is ≥ 21 kg/m^2, with 75 in the control group and 72 in the intervention group. Those who walk outside are all in the intervention group.

Those who take daily medication ≥ 4 are 124 (74% of participants), of whom 68 are in the intervention group and 56 are in the control group.

If we look at the variables with significant p_{values} (p_{value}< 0.05) among those presented in the table, we will retain: HISTORY OF FALLS (p_{value}= 0.046), BMI (p_{value} = 0.022), and OUTDOOR WALKING (p_{value} <0.001). The distribution of the proportions of these different variables between the two study arms is significant.

3. ANALYSIS OF TRAJECTORIES

In order to identify the fall trajectories of participants, we will use methods that allow us to identify individuals in a study population who have the closest profiles. This is referred to as clustering. For longitudinal data, SAS offers a mixed-parametric model developed by Nagin and his colleagues (Nagin, 2014) : Group Based Trajectory Modeling (GBTM). We also have a classification method for longitudinal data in R: K-means, developed by Genolini and colleagues, commonly referred to as KmL (Genolini & Falissard, 2011). These different models offer a range of choices for selecting one model over another based on validation scales, which solves the problem of the number of trajectories that should be retained.

3.1 Group Based Trajectory Modeling (GBTM)

Depending on the nature of our data, GBTM uses an appropriate approach (Nagin, 2014). A Poisson distribution is used if the response variable is a frequency, a censored normal model is used if it is continuous, and a logit model is used if it is dichotomous dependent. GBTM is implemented in SAS software and can be experimented with using the Traj procedure. In our case, we are studying the number of falls every 6 months, which is a quantitative variable, so we will use the censored normal model or CNORM in SAS software (Bimou, 2019).

3.1.1 Results

The fall event was collected in a binary manner. Let x be a participant in the study and $C_i(x)$ be a function that indicates the fall event in month i with $i \in [\![1,24]\!]$ for participant x. It is defined by:

$$C_i(x) = \begin{cases} 1 \; if \; x \; had \; a \; fall \\ 0 \; otherwise \end{cases} \tag{1}$$

This function allows us to construct our fall variable. However, using this variable did not allow us to find interesting clusters to analyze. This led us to explore other possibilities, including:

- replacing our categorical variable (which indicated whether the participant fell or not) with a quantitative variable that gives us the number of falls per month,
- using this quantitative variable to define a function that aggregates the number of falls observed every six months.

Let $D_j(x)$ be the function defined by:

$$D_j(x) = \sum_i C_i(x). \tag{2}$$

The function $D_j(x)$ lists the number of falls of participant x in month j with $j \in [\![1,24]\!]$.

Let $f(x)$ be a function defined by:

$$f(x) = \sum_{j=1}^{6} D_j(x). \tag{3}$$

The function $f(x)$ defined from equation (2), allows us to list the falls of participant x every six months.

The variable **FALL HISTORY** allowed us to have a fifth abscissa, giving us a snapshot of the patient before the start of the study.

We used the censored normal model (CNORM) since our variables are quantitative. We can already note that the algorithm represents the average falls over the study periods, which is not the objective of the study. We aim to identify clusters among our participants who will be grouped based on the number of falls.

The obtained results contain information that seems relevant. We chose the number of trajectories based on the distribution of participants in these trajectories (We set a threshold of 5% in each trajectory).

The obtained fall trajectories considering the entire study population allowed us to distinguish four fall trajectories.

Below are the trajectories characterizing the entire study population (Figure 2):

- Trajectory 1 in red consists of those who have never fallen
- Trajectory 2 in green consists of those with a fall history and who did not fall on average during the two-year study period.
- Trajectory 3 in purple consists of those with a fall history and who fell on average 1.2 times at six months of the study.
- Trajectory 4 in black consists of those with a fall history and who fell on average throughout the study period.

Throughout the study, we will keep the variable **number of falls** defined from the quantitative variable **number of falls per month**. Hence, for all the analysis methods we will use, we will work with the variable **number of falls every 6 months**.

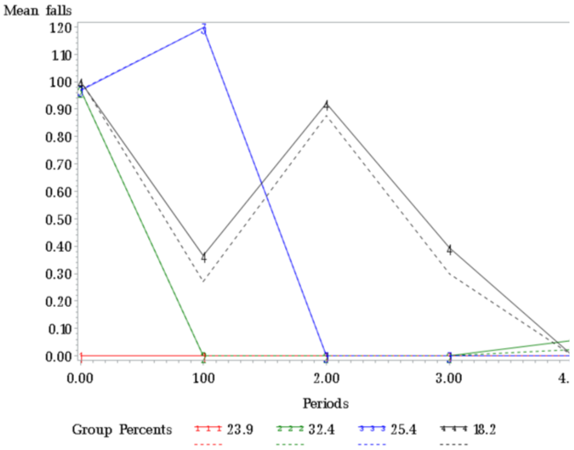

Figure 2. Fall trajectories with GBTM in the total study population.

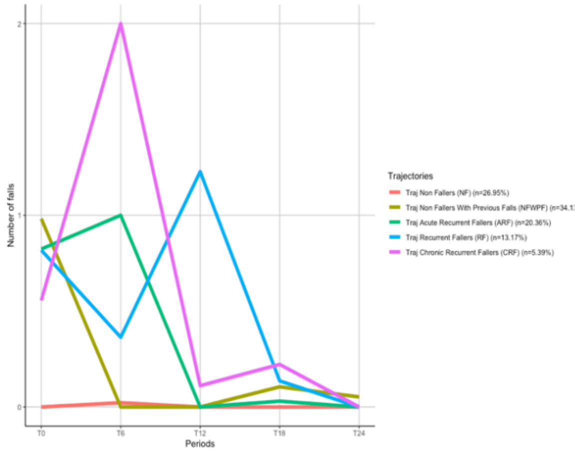

Figure 3. Fall trajectories with K-means in the total study population.

3.2 K-Means Classification (KML) for Longitudinal Data

The KML algorithm is a generalization of K-means clustering on longitudinal data (Genolini & Falissard, 2011). K-means applied to a data set partitions the individuals into subgroups that become increasingly homogeneous by maximizing inter-cluster distances and minimizing intra-cluster distances. It is recognized as an alternative to mixture models. KML performs this classification on data measured over a period, rather than at a single point in time. Implemented in R, KML can use either Euclidean or Manhattan distance to calculate intra-cluster and inter-cluster distances. The choice of model is made using the relevant inertia criterion: the Calinski-Harabasz criterion (Caliński & Harabasz, 1974).

3.2.1 Results

The choice of the five trajectories is made using the Calinski-Harabasz criterion.

In Figure 3, we have the trajectories of the total population falls in the study. We obtained five trajectories that are significant with a minimum threshold of 5% (each trajectory contains at least 5%) of the study population.

Unlike the CNORM of Group-Based Trajectory Modeling (GBTM), the K-means classification represents the number of falls over the study period.

Regarding the interpretation of the trajectories in Figure 3, we will start with the most stable:

- The trajectory of Non-Fallers (NF): it consists of participants who did not fall at the beginning (no history of falls) or throughout the study.
- The trajectory of Non-Fallers With Previous Falls (NFWPF): it consists of participants who fell before the study's beginning and did not fall during the study. Within the first six months of the study, it merges with the NF trajectory.
- The trajectory of Acute Recurrent Fallers (ARF): these are participants who have a history of falls and fell at least once in the first six months of the study. After one year, they no longer fall.
- The trajectory of Recurrent Fallers (RF): It consists of those who have a history of falls and will fall several times throughout the study.
- The trajectory of Chronic Recurrent Fallers (CRF): it consists of the largest fallers in the study. Each participant in this trajectory has a fall history, which did not prevent them from falling up to twice in the first six months. The falls decreased significantly throughout the study, although this trajectory never reaches the NF trajectory.

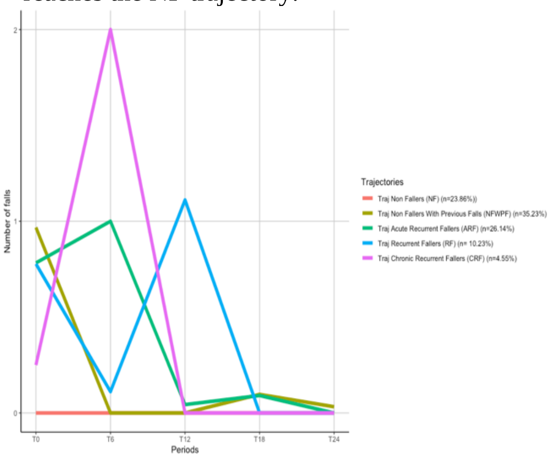

Figure 4. Fall trajectories with K-means in the Intervention Group

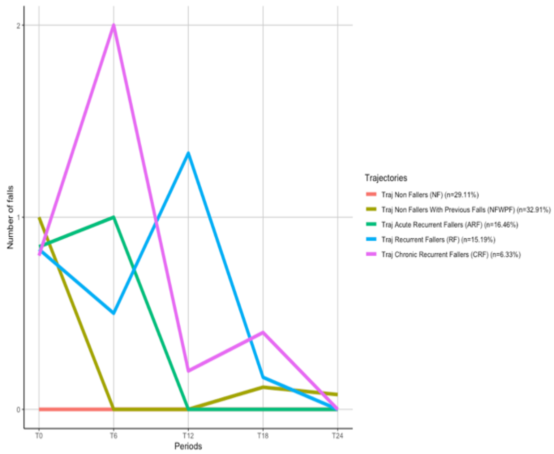

Figure 5. Fall trajectories with K-means in the Control Group

Observing the trajectories of the control and intervention groups allows us to see similar patterns in both Figure 4 and Figure 5 for all trajectories. The trajectories of NF and NFWPF are the same in both figures. If we take a closer look at the NFWPF trajectory in the control group, it starts from 1 at T0, unlike the intervention group where it starts from a lower value. Note that even though the algorithm places the number of falls on the ordinate, the center of a cluster (trajectories are constructed from clusters) is calculated by the average of the points around it. This justifies the fact that the trajectories do not necessarily pass through coordinates whose abscissas and ordinates are integers.

From the first six months, the NFWPF trajectory joins the trajectory of NF in both groups. In the intervention group, they coincide until the end of the study. From the twelfth month of the study, the NFWPF trajectory is distinguished from NF in the control group (Figure 5).

The ARF trajectory has the same pattern in both Figure 4 and Figure 5 even though its value at T0 in Figure 5 is closer to 1. The suspected difference in the first three most stable trajectories becomes apparent with the RF and CRF trajectories. At T6, the CRF trajectories reach a maximum of 2 falls. Meanwhile, the RF trajectories do not reach the same minimum value, indicating more falls in the control arm in the first 12 months.

This trend is confirmed in the second half of the study. The CRF trajectories (at the 12th month) and RF trajectories (at the 18th month) in the intervention group join the trajectory of NF. In the control group, these two trajectories do not stabilize. Here, the stability of trajectories is defined based on the trajectory of NF, which is the most stable (recall that the participants who make it up have never fallen)

4. DISCUSSION

The objective of the work assigned to us was to identify differences that could exist between two randomly defined groups. Describing the study population led us to scrutinize the characteristics that would appear. Using data collected at two different times, UPSAV provided data collected at home, and URCI provided data obtained through telephone calls. We were able to create a database that allowed us to describe the study population and find the trajectories of falls. In order to make the interpretation more fluid, we attempted to give names that summarized the trajectories.

By using the history of falls and transforming the categorical variable "fall or not" into a quantitative variable that records falls every six months for each participant, we found five trajectories of falls using KML. The similarity between the trajectories obtained for the total study population and those obtained for each arm required a comparison.

Until the sixth month of the study, the trajectories of the two groups had slight differences. From the twelfth month in the intervention group, the trajectories of the fallers (ARF, RF and the CRF) converged with those of the non-chronic and non-severe fallers (NF). In the control group, these fallers diverged from the NF. The fact that all trajectories tended towards zero at the end was due to the fact that there were few calls after the last six months.

Since participants in the intervention group had all protocol visits, we can conclude that UPSAV's intervention had an impact on reducing falls in the intervention group from the twelfth month of the study. All trajectories began to stabilize from the twelfth month of the study, except for the trajectory of RF, which started at the eighteenth month.

The effect of UPSAV's intervention was delayed in the trajectory of RF compared to the others. The decrease in falls in the control group is probably due to prevention by the treating physician after a fall. For those in the intervention group, whether the participant falls or not, prevention is provided, which explains the trajectories obtained. From two falls in a year, the participant begins to weaken. In order to provide good prevention, identifying risk factors becomes a priority.

In conclusion we have demonstrated the importance of closely monitoring older adults to prevent the first fall as well as repeat falls for those who have already fallen. This study will allow us to identify risk factors for falls in subgroups (within each trajectory of the study) of the total study population. The predictive factors for falls identified in each trajectory will enable specialists to better understand the profile of fallers and thus provide more targeted prevention strategies for patients. What are the predictive factors in each of our trajectories? Will these results be more meaningful with more data? The limitations of the study include the sample size and the recruitment of participants only in France. Telephone calls also posed challenges in data collection.

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