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A multidimensional data decision support system based on fuzzy logic for risks prediction of elderly people living in nursing homes.

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CONTENTS

1. INTRODUCTION

In the area of health care, a major issue is the provision of adequate and effective health conditions for the elderly, as people aged 65 and older are the fastest growing segment of the population. [1] A prediction of the life expectancy, estimated by the United Nations Department of Economic and Social Affairs Population Division (UN DESA), results in an increasing mean of over 80 years old for most of the countries in the next decades. By looking just at the data related to Italy, research conducted by Istat shows that in the following years there will be a share of over 65 year olds close to 34%, with a mean people age increasing at 52 years old.[2] At an older age, there is an increasing need for long-term care (LTC) and facilities to assist elderly people because their likelihood of disability increases and hence their gradual loss of body function. In fact, other researches show that after acute admission, 20–30% of older patients experience a functional decline, which is associated with nursing home placement, poor quality of life, increased costs of care, readmission, and mortality. [3], [4] Nursing home residents are often frail since their multiple physical and cognitive deficits place them at high risk conditions. Especially for them, an alert prediction system is an assistive technology that will deliver appropriate escalation in the earliest time so that old people can receive immediate responses. Early detection of changes in the health condition of the elderly can increase their safety, and the possibility to perform a risk prediction based on previously acquired information represents a powerful tool in order to detect critical conditions in time.[5], [6]
The purpose of this project is to develop a digital platform (called *CareAI*) to improve the quality of care and well-being of residents, family members, and care assistants in nursing homes, increasing care services quality and efficiency. Specifically, expected impacts of the platform implementation are:

- Reduction of *Adverse Events* such as falls and other possible risks.
- Reduction of *Infections, Sores,* and complications from respiratory diseases.
- The improvement of *work quality* for the care assistants, thanks to a multidimensional approach for monitoring and classification of the events that could improve the work organization
- Reduction of residents' *loneliness* thanks to the use of tablets which will allow access to resources for communication and entertainment.
- Reduction of the caregivers' burden thanks to the use of communication channels with the nursing homes accessible from tablets and other mobile devices.

This thesis, in particular, is focused on the reduction of adverse events in the elderly, describing the analysis of the main risk factors for old people living in nursing homes, the different techniques

used to acquire the necessary information with a multidimensional approach, and the development of a prediction model based on an expert system, with the help of a Fuzzy Inference System (FIS). The data will be collected from different information sources distributed in the nursing homes, and these sources are divided into:

- Environmental sensors for air quality detection.
- Audio and video data collection and analysis.
- Registration of activities and general information on tablets performed daily by an operator.

The integration of these pieces of information will allow the proactive management of many clinical issues. In the following chapter, there is a resume of literature information related to IoT devices, evaluation scales, and the most common methods for analysis and prediction based on data.

2. LITERATURE

This chapter describes the main techniques already in use in order to analyse, monitor, and provide an efficient analysis and control of people living conditions. The first focus is on the most used Internet of Things (IoT) devices and their best possible application in old people lifestyle; the second part describes what types of the questionnaire are used to define an accurate physical and psychological picture of the clinical condition of a person, and what is the approach used on this project. Finally, the third part is describing the most common machine learning approaches employed in the prediction and classification of data related to old people and a description of the approach applied in this project with a brief focus on what is a FIS.

2.1. IoT DEVICES

Several surveys have been written on sensors for ambient assisted living systems. IoT sensors in healthcare are divided into two different groups: *Ambient sensor-based* and *Wearable sensor-based*. The latter can measure important parameters such as heart and respiratory rate, velocity and acceleration, body temperature, oxygen saturation and so on. Ambient sensors instead are embedded into the environment and collect different types of data to model the activities or events of the smart home users.[7] The following picture shows an example of a setup scheme of a smart home for monitoring the behaviour of an elderly person. There are different kind of sensors like pressure, motion, vibration, and sensors that will keep tract of the person behaviour inside the house.

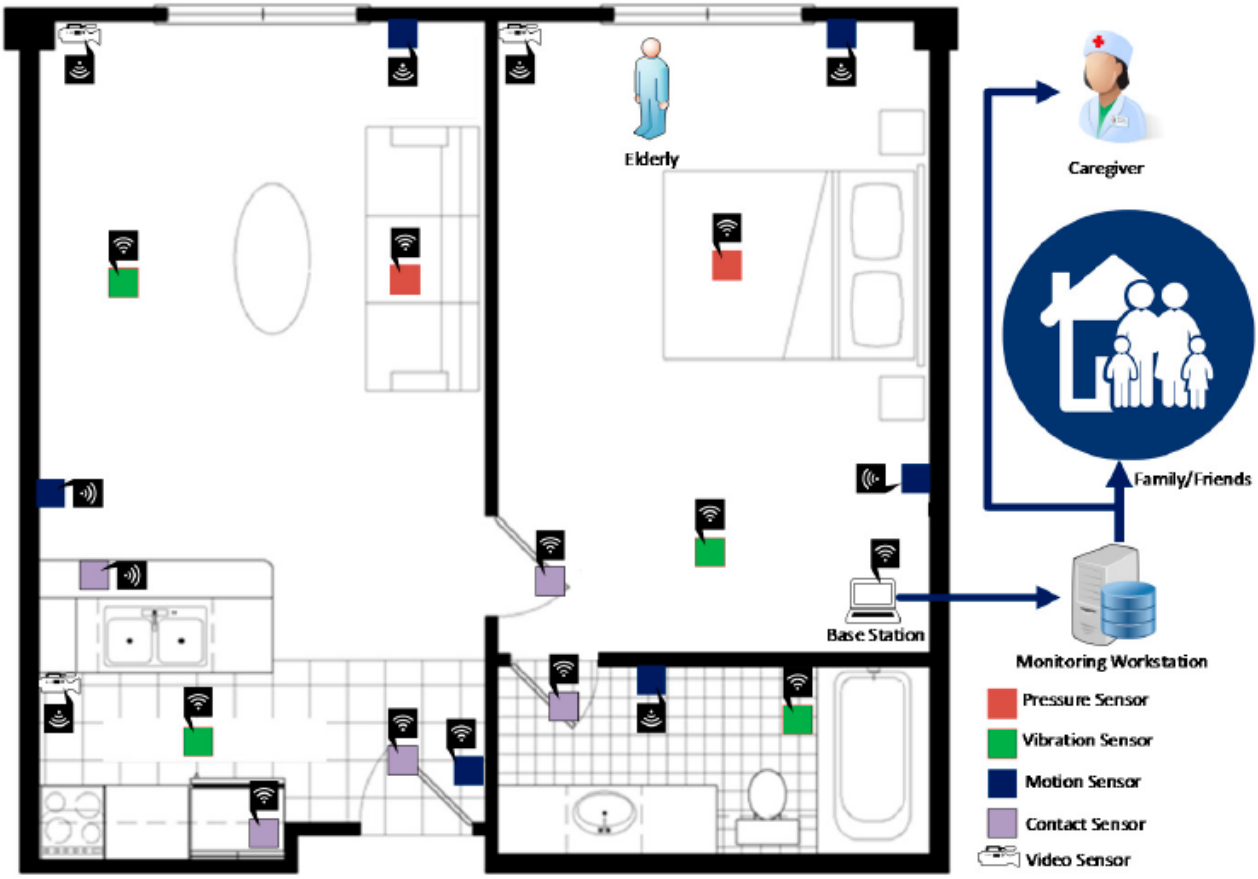

Figure 1:Scheme setup for old people care monitoring based on different ambient sensors.

Gushima et al.[8] describe the following system design to recognize assisted daily living activities (ADLs) according to sensing data. They perform ADL context modelling to create predefined basic rules for recognizing the activities of old people as it is shown in figure 2.

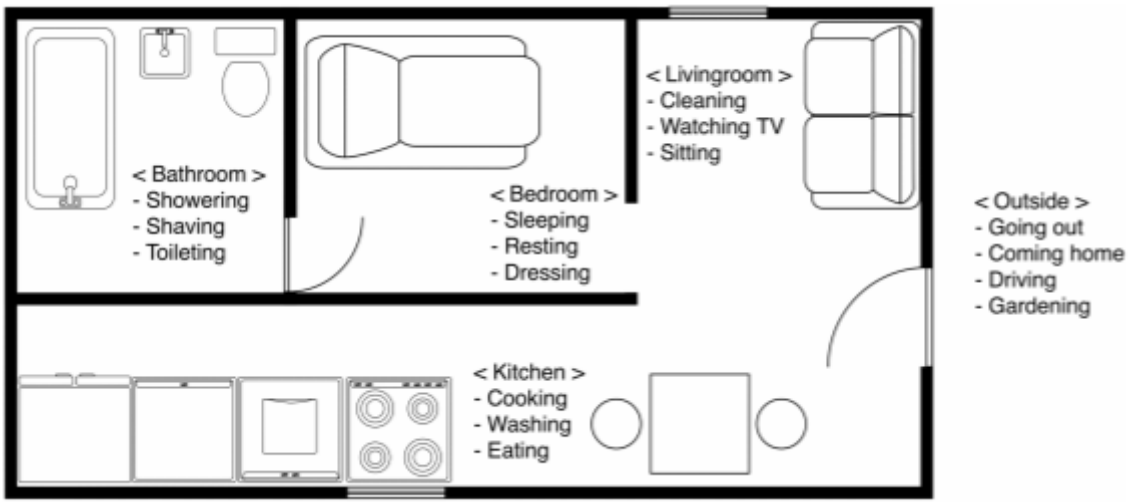

Figure 2: ADLs context modelling example.

Most of the sensor-based surveys focus on wearable sensors or combine them with ambient sensors, that because the data collection process using wearable sensors is usually easier than the one using ambient sensors. For example, Pierleoni et al. [9] propose a fall detection system based on a triaxial

accelerometer, gyroscope, and magnetometer wearable on the waist. Another study describes and compares sensors like the smart wearable bands, smart socks or smart watches to monitor old people with Alzheimer.[10]

However, wear sensors on the body could be a restriction for old people, and so discourage them of using these types of sensors. Some disadvantages like an uncomfortable feeling during long-term skin attachment can occur, or instead, the fact that accurate data recordings with wearable sensors may require a professional adjustment of the sensor on the patient body. Hence, ambient sensors seems to be an appropriate and reliable choice for helping and monitoring old people.[7] Surveys identified five main ambient sensor types:

- *Passive infrared (PIR) motion sensors* to detect the movements of individuals based on a variation of temperature.
- *Video Sensors*
- *Pressure sensors,* which are applied to detect the presence of residents in beds or on chairs.
- *Microphones*: are employed to detect different events like the falling of a person or an object. This type of sensor could be placed also on the floor.
- *Radar Sensors*: it is utilized for its better perception of elderly people compared to vision-based sensors since it can penetrate strong obstacles. Furthermore, it does not affect the subject privacy.
- *Combined Ambient Sensors* or *Combined Ambient and Wearable Sensors*.

Despite many structures have already begun to use digitalization paths in their working organization, there is still a gap between the hospital sector and the elderly healthcare sector. [11] Thus, unlike the hospital industry, the residential care sector faces many weaknesses in digital improvements. In this context, it is necessary to find innovative solutions to foster innovation, and to improve the employed technology in nursing homes.

By focusing on this project, the main sensors used are: Video Sensors, Microphones, Pressure sensors place on the guest bed, and Volatile Organic Compound Sensors (VOCs) that directly measures ambient concentrations of a broad range of “reducing gases” associated with bad air quality.

2.2. HEALTH CONDITION EVALUATION SCALES

Since at the base of the psycho-social and clinical complexity of the frail elderly there is the interaction of the different "dimensions", the multidimensional evaluation called VMD (from Italian terminology “Valutazione Multidimensionale”) is identified as a good performance tool for

the diagnosis of frailty.[12] VMD is implemented to investigate different fields such as functional disability, cognition, mood, nutritional status, comorbidity, the risk of falling or the appearance of pressure sores, housing status, and the social and welfare context of the subject. This tool has the advantage of being validated for many elderly subjects with different characteristics. Also, it is simple and quick to perform, widely used, and therefore comparable both in the clinical and research fields. Many researchers were conducted on old people's health conditions by using assessment scales, to prove their utility in the evaluation of care assessment. Veyron et al. study evaluates tools include the Adjusted Clinical Groups (ACG), the Community Assessment Risk Screen (CARS), and the Elder Risk Assessment Index. [13] these tools works with individual characteristics recorded at a specific point in time like VMD, and have been found to be effective in predicting the risk for 7-day and 14-day emergency department (ED) visits. [13] Kuspinar et al. study validates a prediction algorithm for first-time falls by using the Resident Assessment Instrument-Home Care (RAI-HC) among home care clients who had not fallen in the previous 90 days. The RAI-HC is an assessment system for patients that includes the Activities of Daily. Living (ADL), the Pain Scale, and the Cognitive Performance Scale,.[14]

In this project, the VMD defines the following aspects for each subject and its evaluation is performed each 6-12 months:

- *General condition* of the guest: like body weight, the Body Mass Index (BMI), and possible diseases.
- *Special therapies* that the guest needs such as dialysis, assisted breathing, or radiotherapy.
- *Assisted Daily Living (ADL)*: This term describes the skills that are fundamental to independently care for oneself such as mobility, bathing, and eating.[15]
- *Cognitive/Emotional state*: A series of questions to understand how the subject thinks, learns, and remembers together with how he interprets and responds to emotions (both pleasant and unpleasant).
- *Respiration/ Nutrition*: If the guest has special needs like a gastric tube or if he has dysphagia.
- *Norton scale*: A scale used to predict the likelihood a subject will develop pressure ulcers by using the following five criteria: activity, mobility, physical condition, incontinence, and mental condition.[16]
- *Skin conditions and continence*: evaluation of redness, wounds, ulcers of different severity.

Thanks to the patient information contained in the VMD, it is possible to build a specific treatment plan for each guest in nursing homes, since in most cases old people present multiple chronic diseases that differ from each other. This is the so-called *Individual Service Plan* (ISP). It defines daily tasks, parameters, monitoring, and verification tools that the guest or the operator (also with

family members) will follow when requested. The use of a personal approach allows a closer, central and sensitive management to the patient, for in-depth knowledge of his/her aspects of life and his/her well-being. [17] ISP is also present in this project, and it provides information that will be discussed in the following chapters.

2.3. COMMON METHODS FOR ANALYSIS AND PREDICTION

Machine learning (ML) and Artificial Intelligence (AI) based approaches have the potential to significantly help the analytic and decision-making processes involved in clinical caregiving. The aggregation of healthcare data sets thanks to a multidimensional approach leads to a much more information-rich base pattern in the data which would lead to enabling a wider set of predictions, with better accuracy and features.[18] By using sensor-based information or data from questionnaires, different applications have been developed in the prediction of old people's risk conditions. Just to give some examples, J. Cook et al. paper studies smart home technologies to provide at-home health monitoring with the following purposes: identifying lifestyle trends (ED algorithm), detecting anomalies in current data (Active LeZi algorithm), and designing a reminder assistance system (Hierarchical Partially Observable Markov Decision Process).[19] Other approaches diffused in the literature that show good results are: linear regression model to prevent functional decline [4], bagging and boosting methods, two ensemble techniques which combine many models' predictions able to identify the social frailty status of the elders [20]. Decision trees (DT) and random forest (RF) seems also applied a lot to the risk prediction field, and in particular, RF results appears very good with respect to other algorithms. [4], [6], [13], [14], [20], [21], [22], [23]

In this project, an expert system based on fuzzy logic seems to be the best solution for the risk prediction, and the reasons will be discussed later together with the results. The following part describes what an expert system means, what is a fuzzy inference system and how it works.

2.3.1 Expert System

An expert system (ES) is a knowledge-based system that mimics human knowledge by using an inferencing procedure through the application of AI technologies. ES allows managing problems that would otherwise require human expertise. In fact, his name depends on the fact that it can solve any complex problem of a specific domain since it contains an expert knowledge of that domain. In building an expert system, the usual steps are: [24]

- Problem selection,
- Knowledge acquisition,

- Knowledge representation,
- Knowledge encoding,
- Knowledge testing and evaluation,
- Implementation and maintenance.

ES is a powerful technique for its specific knowledge, but also for this reason it presents some challenges during knowledge acquisition to build its basis. It is difficult to transfer the expert knowledge into the system since the experts themselves are not able to codify their own knowledge sometimes. For this reason, this process requires collaboration between experts and programmers to obtain a final knowledge base. The fuzzy inference system used in this project is an example of an expert system since it is constructing in collaboration with some experts of the domain.

2.3.2 Fuzzy Inference System

A Fuzzy Inference System (FIS) is described by a set of rules defined with *if-then* conditions. Its method of reasoning resembles human reasoning since it involves all intermediate possibilities between the crisp values "yes" and "no" by using a range called *membership function*. The working principle of the FIS consists of:

1. A *Fuzzification* that converts all input values into fuzzy membership functions.
2. A knowledge base: a collection of rules-based and databases are formed to compute the fuzzy output functions.
3. A *Defuzzification* process that converts the fuzzy output function to get "crisp" output.

Fuzzy sets can be represented graphically, by assigning them different membership function values. This is a way to represent words that constitute these sets, and an example is reported in the figure below, where each fuzzy sets correspond to a linguistic term like *"very low" "low" "medium" "high" "very high"* represented here with a trapezoidal shape.

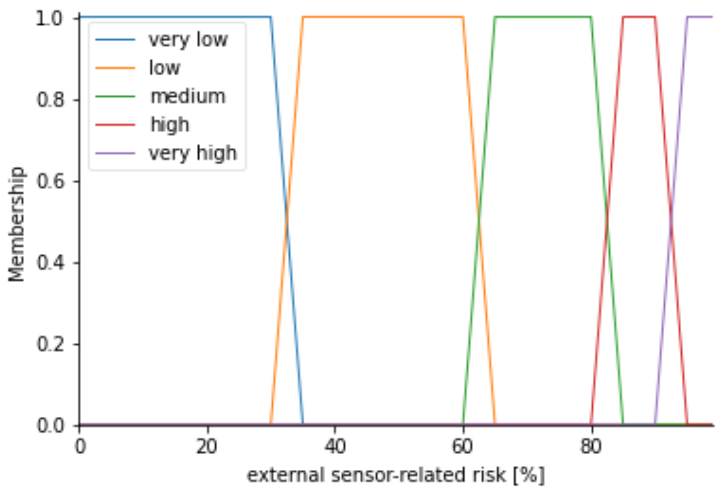

Figure 3: Example of fuzzy sets representing terms very low, low, medium, high, and very high with a trapezoidal shape.

The definition of a membership function μ is:

$$\mu_F : U \rightarrow [0,1]$$

Related to fuzzy set F on the universe of discourse U. Each value between this interval is representing a *degree of membership.* When the degree of membership is 1 it means that the value belongs entirely on that fuzzy set, while if the degree of membership of that value is 0 then it does not belong to the given fuzzy set. The values between 0 and 1 correspond to the degree of uncertainty with which the value belongs in the fuzzy set.

The trapezoidal membership function is described in this mathematical way:

$$\mu_S(x) = \begin{cases} 0, & x < a \\ \frac{x-a}{b-a}, & a < x < b \\ 1, & b < x < c \\ \frac{d-x}{d-c}, & c < x < d \\ 0, & x > d \end{cases}$$

where $a < b < c < d$ real scalar parameters.

The following block scheme helps to understand the working principle of a FIS: The Rule Base which contains fuzzy if-then rules, the Database that defines the membership functions, the decision-making unit that performs operations on rules, the Fuzzification inference unit which converts crisp quantities into fuzzy quantities, and at last the Defuzzification inference unit that converts fuzzy quantities into crisp quantities.

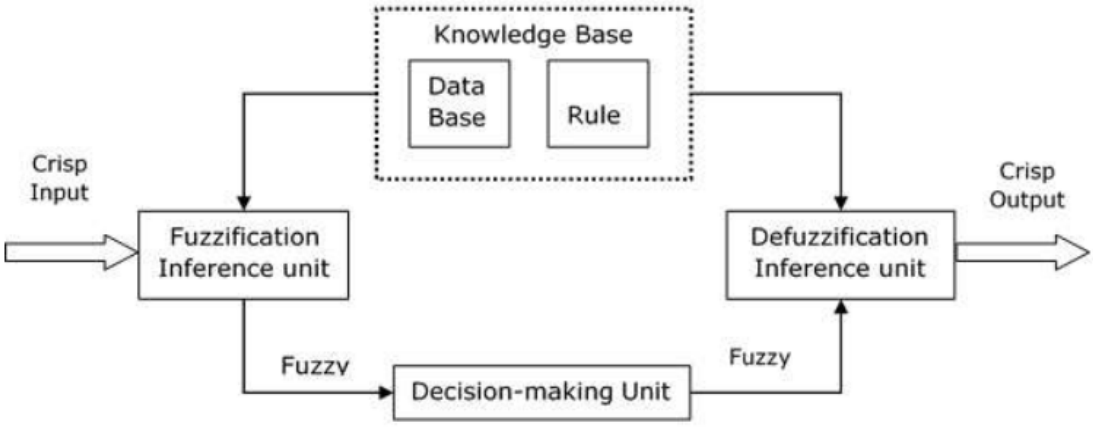

Figure 4:Five functional block describing a FIS.

In this context, the inputs and their linguistic terms in the *'if'* parts of the rule base are called '*antecedents'*, and the outputs, called '*consequents',* correspond to the *'then'* part of the rule base.[25]

There are two main important techniques of FIS: the Mamdani Fuzzy Inference System and the Takagi-Sugeno Fuzzy model (TS).
Mamdani fuzzy inference is the first and most used method. This system has an intuitive and easy to understand rule-bases, and the output of each rule is a fuzzy set. So, Mamdani systems are well-suited when the rules are created from human knowledge, for that reason they are perfect for developing expert systems but more specifically in medical diagnostics.
Instead, the Takagi-Sugeno-Kang fuzzy inference system (TS), has fuzzy inputs but a crisp output called a singleton. Since its defuzzification is more computationally efficient than the Mamdani model (because it performs a weighted sum of a few data points), it suites well in control problems. Anyway, in this project, the Mamdani method is applied since the dataset contains medical and healthcare data.

Fuzzy logic is an important concept when it comes to medical decision making because its logic-based approach has great potential in this field. It is important to note that since this system is an Expert system, it contains heuristic knowledge its knowledge-base, so it requires rules of thumb used by the experts who work in that specific domain. In particular, the experts define the thresholds and the linguistic quantity of each value described in the experimental protocol section. And even after the definition of the membership functions and the parameters, they could be adjusted and updated later during the process in order to improve the functioning of the system. [26]

3. EXPERIMENTAL PROTOCOL

As previously said, the models developed in this project constitute a part of a software called "*CareAI*". Its specifics are the following:

1. The presence of algorithms/models for the processing of new information, starting from the data structure described below. Plus, the whole system is implemented in a way that considers future expansions.
2. The ability to access services easily, through simple client-server communication.
3. A data updating phase able to manage itself autonomously and periodically, through a request to the management system.
4. The storage of all the resources necessary for data analysis.
5. The system needs to be portable: in particular, everything is encapsulated in a Docker Container.

CareAI is implemented in Python. It appears a good choice since Python libraries represent a good basis for data analysis and the development of other functionalities. Some of the libraries used in

developing this software are *Skfuzzy* for developing the FISs, *NumPy* for all the mathematical operations, *Flask* for web-server development, *matplotlib* for visualization, *Pymongo* for interfacing with MongoDB, or *Requests* for managing HTTP. These parts are investigated in detail in the following chapters, together with a description of the structure of the dataset and a description of the risks and how they are investigated.

3.1. DATA

In order to receive the data from the external software, a Representational State Transfer Application Program Interface (RESTful API) is implemented. An API allows two software programs to communicate with each other, and REST is an architectural style often used in web service development by using HTTP requests to access and use data with methods like:

- GET: to get target resource's state representation
- POST: Let the target resource process the representation enclosed in the request.
- PUT: Set the target resource's state to the state defined by the representation enclosed in the request.
- DELETE: Delete the target resource's state

The database is managed by using MongoDB, a source-available cross-platform document-oriented database program. MongoDB stores data records as BSON documents, where BSON is a binary representation of JSON (JavaScript Object Notation) documents, though it contains more data types than JSON. In this way, documents are composed of field-and-value pairs and have the following structure:

```
{
field1: value1,
field2: value2,
field3: value3,
...
fieldN: valueN
}
```

The data are divided in two main collections called *Guest_data* and *Event_data*. The first one contains in turn a different collection for each guest, and all the subparts are referenced to the correspondent guest by its identification (*id*). This is the main structure of a collection for a single guest containing cllections related to all its information:

```
{
  "guest_data" : [{
    "guest_id":"0|1",
    "medication":[{...}],
```

"medication_time":[{...}],
"event":[{...}],
"val":[{...}],
"isp":[{...}],
"measurement":[{...}],
"act_event":[{...}],
"guest_info": {}
}]}

The *Medication* field contains information about what type of medication the subject takes, the start and stops date of assumption, the assumption modality (oral, intravenous, etc.) and with which frequency (daily, monthly once each weekend, etc.). The *Medication_time* field has information about at what time the medication was taken, whether before or after meals, and in what quantity. This field corresponds to the confirmation that the drug administration has taken place. *isp* field contains all the activities foreseen by the ISP that should be carried out for that guest, and the *act_event* field corresponds to the confirmation that these activities have taken place. *Event* contains unforeseen situations that can happen (like the occurrence of infection), and the *val* field contains all VMD values described in chapter 2.2. The *Measurement* field contains values like subject weight, height, glycemia, Oxygen saturation (SpO2), and blood pressure with the correspondent id and acquisition data. Finally, the *guest_info* field has general information about the guest like its room, education, marital status, and so on.

The second collection *Event_data* refers to all the information coming from environmental sensors and has a structure as reported below:

"event_data":[{
"id": "0|3",
"insert_date": "2020-12-06T02:40:01.646Z",
"room": "102",
"detection_type": "Video",
"value": null,
"start_time": "02:40:1",
"end_time": "03:15:49"
}]

This collection example refers to a specific guest *room* (102), and the *detection_type* field gives the information about the type of sensor (Video, Microphone, Air, Temperature, or Humidity sensor). *Start_time* and *end_time* represent the initial and final acquisition time respectively, and *insert_date* reports the acquisition date. If temperature or humidity information is recorded, for example, they show their measure in the *value* field.

3.2. RISKS DEFINITION

This chapter describes the old people related risks and how they are estimated. All the following evaluations are performed by the help of human experts who work in the domain; they were able to identify the main dangerous scenarios in nursing homes and what may be the warning signs for them.

Ten risks condition are obtained in this way, and there are:

1. Risk related to wrong assumption of medication
2. Fall risk
3. Suicide risk
4. Lack of care procedures
5. Risk due to poor quality of the microclimate
6. Risk of malnutrition
7. Risk of aspiration pneumonia
8. Risk of damage or injury due to a fight between residents
9. Escape risk
10. Risk of injuries due to pressure sores

3.2.1. Risk of the wrong assumption of medication

This scenario takes into consideration the risk that the guest may suffer serious damage because of incorrect drug therapy. In particular, cases are identified in which the therapy is prepared without following the updated indications of the newest medical prescription, or if the medication is administered to the guest several times, it is not administered, it is not taken by the host or it is administered to another guest by mistake. The nurse directly accesses the guest's therapy card being already updated with the doctor's latest prescription when preparing the therapy. During administration, the nurse must mark that the prescribed drug, in the prescribed doses, has been correctly taken by the guest and check on the tablet that administration and intake have taken place correctly. The operation thus detected will also allow other operators / nurses to see that the activity has taken place correctly. Guests at risk are identified as all those for whom *a problematic assumption of medication is detected for seven consecutive days.*

3.2.2. Fall risk

This scenario considers the risk that the guest may fall and consequently suffer serious damage for it. In particular, the following cases are identified:

- *Number of risings at night*: the guest gets out of bed several times during the night (from 10pm to 5am). When he gets up more than twice a night for at least 3 consecutive days, there is a risk condition.
- *An agitation state*: It results present (night only) at least once a day in the last 4 days. This state is detected through one or more of the following variables:
  1. *High beats* (> 40 beats compared to baseline for at least 3min), where the baseline is the min bpm recorded from the subject in the previous 7 consecutive days.
  2. *Vocal noise* detected during night with a microphone (the information is relevant for the agitation state when the moans persist for at least 30 consecutive minutes).
- *Blood pressure values* out of range: It is detected for at least 2 consecutive days with values outside the threshold (systolic pressure lower that120 mmHg or higher than 160 mmHg; diastolic pressure higher than 90 mmHg or lower than 60 mmHg).
- The guest *wanders* during the night for more than 30 minutes consecutively for at least 3 days.

The presence of one of these situations is enough to have a fall risk condition, and the simultaneous presence of more than one of the cases listed above increases the probability.

3.2.3. Suicide risk

This scenario takes into consideration the risk that the host may commit suicide due to his emotional state. It is evaluated by *monitoring of the emotional state* through the responses indicated in the last recorded VMD ("Is the host depressed?", "Does he refuse assistance?" These two conditions must be present at the same time). It is also important to consider if *malnutrition* has been detected (if the food intake results lower than 50% of the meal) for at least 5 consecutive days. This situation is connected to the case n° 6 which reports the risk of malnutrition.

3.2.4. Lack of care procedures

This scenario reconstructs the risk that the guest may suffer serious damage because of the lack or incorrect execution of activities provided by the operators / nurses. These activities are stored in the ISP section of the subject profile and they must be ticked off when they are performed correctly. If some activities (mainly related to personal hygiene) are not performed correctly, this can start an infection that can lead to an epidemiological cluster inside the nursing home.
The risk is present if some activities are skipped for two consecutive days Also, it is important to check if there are infections for each guest in the last 60 days, and then check if more patients (2 or more) have the same infection. In this case there is a risk that some operators are performing activities in the wrong way.

3.2.5. Risk due to poor quality of the microclimate

This scenario considers the risk that the guest may suffer serious damage as a result of a poor quality of the microclimate. The following cases are considered:

- Measurement of *ambient temperature and humidity* for a consecutive period of 24h above the following values:
  1. *Temperatures* out of the ideal range (18 ° -22 °)
  2. *Humidity* > 70%
- detection of the state of agitation (defined as above in the second scenario, but here is considered during 24h)
- *COPD* (Chronic Obstructive Pulmonary Disease) and / or *heart failure* are present among the pathologies reported in the VMD.

Considering these aspects, it is possible to identify a guest at risk due to poor quality of the microclimate when anomalies are detected in the temperature and humidity values of the room. The presence of the other two parameters does not constitute a risk factor individually, but the simultaneous presence of the case listed above with these latter increases risk probability.

3.2.6. Risk of malnutrition

This scenario considers the risk that the subject may suffer serious damage because of malnutrition. In particular, in the event that the guest does not eat the expected amount (*food intake <50%* of the meal) for at least 5 consecutive days, or a detection of a *decrease or increase in weight* higher than 3% in a period of only 30 days. The simultaneous presence of one or more of these cases increases the probability of subject malnutrition only in the case of weight reduction, otherwise the weight variation is a condition sufficient for malnutrition risk.

3.2.7. Risk of aspiration pneumonia

Aspiration pneumonia, or “Ab Ingestis”, is a type of lung infection that is due to a relatively large amount of material from the stomach or mouth entering the lungs. Signs and symptoms often include cough or fever.[27] This scenario considers the following situations:

- Detected through *nocturnal coughs* for at least an interval of 5 minutes total during the night, a check is also detected on the "monitoring of oral cavity cleaning" activity (present in ISP) carried out during bedtime.
- State of agitation detected as in the case of risk of falling.
- The subject is suffering from dysphagia and / or dementia and / or Parkinson’s diseases.

The fist condition is enough to identify the subject at a risk of aspiration pneumonia. The presence of the other two parameters does not constitute a risk factor individually, but the simultaneous presence of the case listed above with these latter increases risk probability.

3.2.8. Risk of damage or injury due to a fight between residents

This scenario considers the risk that the subject may incur on a fight between residents. The fact that the subject is *agitated* and that he may be *violent* is considered. The latter is detected through his/her VMD and specifically in the *behavioural disorders* section (questions relating to physical verbal aggression and inappropriate behaviour). If both these parameters are present, there is the possibility that a fight could occur.

3.2.9. Escape risk

This scenario takes into consideration the risk that the guest could suffer serious damage after he escapes from the nursing home. This evaluation is done by considering if the guest is suffering from dementia, if the guest is agitated, and if the guest wanders during the night for more than 30 minutes consecutively for at least 3 days. Dementia is a chronic syndrome in which there is deterioration in cognitive function, and its presence is the main parameter to assess the risk of escaping.[28] The presence of the other two parameters does not constitute a risk factor individually, but the simultaneous presence of the cases listed above with these latter increases risk probability.

3.2.10. Risk of injuries due to pressure sores

This scenario considers the risk that the subject may suffer serious damage because of pressure sores. It occurs in the case in which the subject that lays in bed is not mobilized or raised when expected, and that his hygiene is not carried out properly. As in the risks defined above, the simultaneous presence of these cases increases the risk probability.

3.3. RISK MODELLING

Some of the risks defined in the previous chapter requires a check of information reported as ticks off different lists, so they are implemented with function composed by *if chains*. Each morning the database is refreshed with the new information collected during the previous day. These information pass through the algorithm and each function checks whether its statements are respected or not. Since most of the events need to happen for some consequent days to be relevant for the assessment of the risk. If the statement results true, the information is stored in an external JSON file to keep tract of it. After the amount of days reach the defined threshold, the algorithm recognizes it and

send a video message on the main software to advise the operators of the risk condition. Risk possibilities are displayed as follow:

"Guest identification code": "Alert message with the relative Risk information"

With exception for the risk of falling (risk n° 2), the risk related to the microclimate (risk n°5) and risk of escaping (risk n°9) the alert system divides the risk conditions into 2 groups based on their gravity: Medium Risk and High Risk. The picture below reports an example of output during a test, where we have a different risk condition that occur for each different subject:

```
0|1 : Rischio Grave danno dovuto ad errori di terapia farmacologica
0|2
Rischio di possibile caduta: 77.0 %
0|3 : Rischio Suicidio per stato emotivo
0|40 : Rischio  GRAVE mancate procedure assistenziali
0|40 Rischio ALTO Grave danno da LDD
0|41 : Rischio  MEDIO mancate procedure assistenziali
0|41 Rischio ALTO Grave danno da LDD
0|5
Rischio correlato all'ambiente: 76.0 %
0|6 : Rischio MEDIO Grave danno dovuto a malnutrizione
0|7 rischio ALTO Grave danno o Morte dovuta ad ab ingestis
0|8 Rischio lesione dovuta a colluttazione tra residenti
0|9
Rischio correlato alla fuga dell'ospite dalla struttura: 74.0 %
0|10 Rischio ALTO Grave danno da LDD
Rischio infezione diffusa tra i pazienti, id infezione: ['0|1', '0|2', '0|4']
```

Figure 5: Output test for each of the 10 risks conditions, related to different patients.

As it is possible to see in this picture, for three of these cases a percentage is showed up with a percentage. That because the output variable of the model here is represented by a fuzzy index that states the risk level of a particular condition. That is performed since these risk conditions requires a huge amount of inputs to be computed, and so the description of the FISs is discussed below.

The number of fuzzy rules defined depends on the possible combination of membership functions. So, a FIS with *j*-input variables has R rules defined as:

$$\boldsymbol{R = p^{j}}$$

Where p is the number of linguistic terms per input variable. As the complexity of a system increases, the size of the rule base increases exponentially.[29] For this reason, in this project different FIS are implemented one chained with the other to perform the risk evaluation with all the necessary inputs. All the rules employed in these systems are reported in Chapter 5.

3.3.1. Vocal noise

To evaluate the patient agitation state, a microphone records sounds in its room to detect his laments. Figure 6 shows a logic representation of the FIS; its output is in form of a percentage and it will constitute an input in the following risk systems.

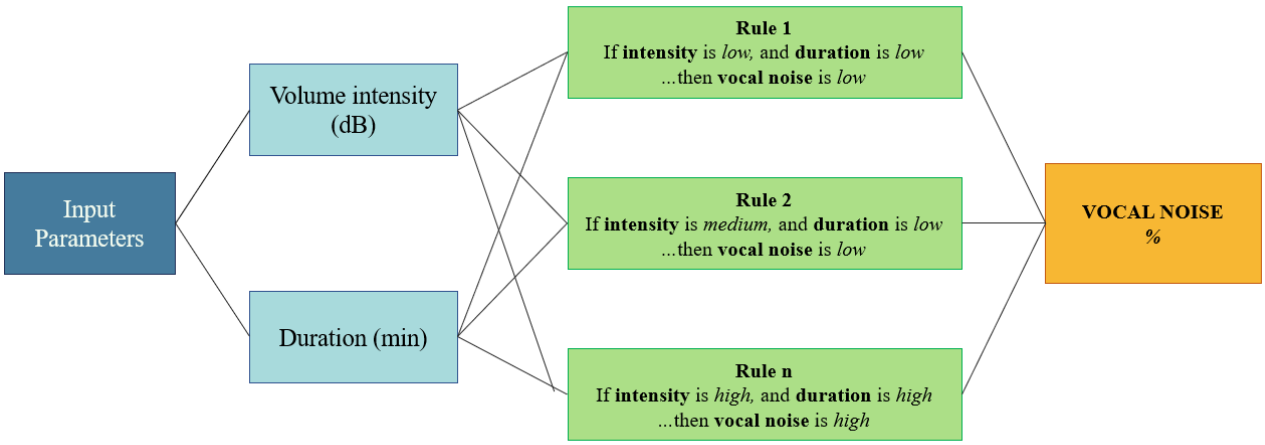

Figure 6: FIS block scheme representation for evaluation of vocal noise.

The volume intensity is in dB with a range between 0 and 75 dB (normal conversation has usually a value of 60 dB).[30] The duration means for how long the voice is heard. Below fuzzy sets for two features involved in vocal noise description are shown. All the rules related to vocal noise definition are reported in the *Appendix A*.

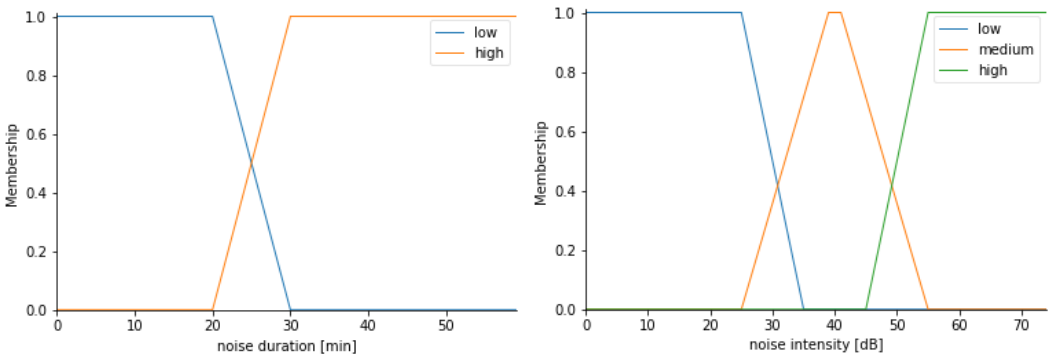

Figure 7: Membership functions of noise duration and noise intensity. The first graph divides the recorded noise duration into "small" and "high", the second graph divides the dB intensity in 3 sets: "low", "medium" and "high".

3.3.2. Risk of Falling

To evaluate the risk of falling there are many different inputs, as it is reported in chapter 3.2. So, these inputs are divided into two FISs, one refers to the sensors-related inputs while the other has physiological parameters as inputs. Fuzzy sets for the input features are reported here in figure 8, the *Vocal noise* input corresponds to the output of the FIS described in the chapter 3.3.1, in the form of a score (between 1 and 100).

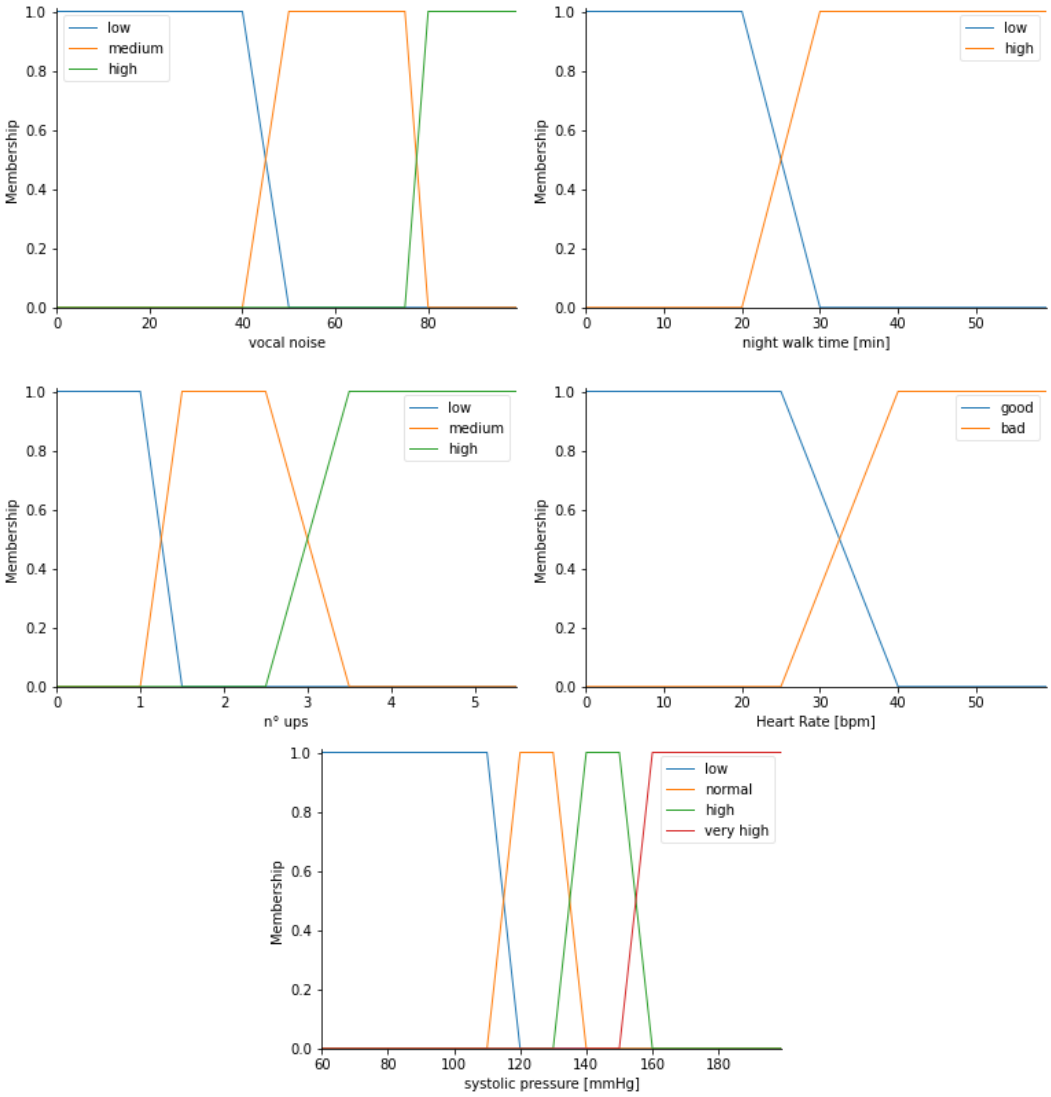

Figure 8: Membership function correspondent to: Vocal noise, duration of walking during night, number of ups during night, Heart rate variation, and blood pressure.

Vocal Noise divides the output from the previous FIS into 3 sets: “low”, “medium” and “high”, night walk time is divided into 2 sets for small-time and high-time duration of night walking. The *number of ups* is also divided in 3 sets labelled: “low” (when the subject stands up 0 or 1 time during night), “medium” and “high”. The *Heart rate variation* (with respect to the basal value) has 2 sets called “good” and “bad” if the variation is high. Finally, the *blood systolic pressure* is divided in 4 sets called “low”, “normal”, “high” and “very high”.

All the rules related to this risk assumption are reported in the *Appendix B*.

The following block scheme gives an idea of how the final fall risk system is implemented. The output variable of the model is represented by a fuzzy index that states the risk level which is in the form of linguistic ratings described as “Very Low”, “Low”, “Medium”, “High”, and “Very High”.

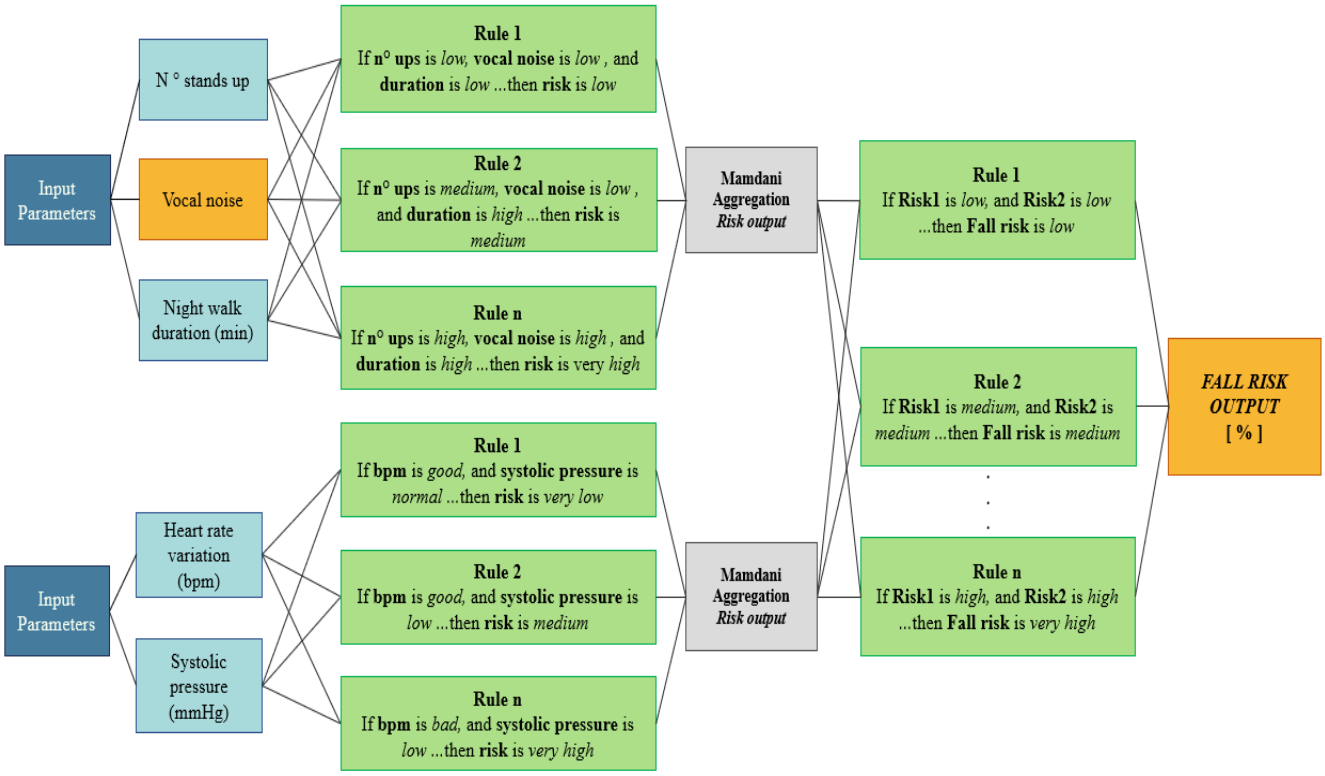

Figure 9: Block scheme of FISs for prediction of Risk of falling.

In the figure below, the output surface of the system based on the input sets is shown. With helpful use of Matplotlib and repeated simulations, we can observe what the entire control system surface looks like in three dimensions. Surfer viewer is a three-dimensional plot that allows to see the relationship between the final fall risk index with respect to the sensor-related risk values (microphones, video etc) set and the set corresponding to the physiological condition (bpm, systolic pressure). It is possible to see from the picture that physiological information seems to have a higher weight during the evaluation of the final fall risk output as the higher values for the risk of falling has higher percentage values for higher values of that input (yellow part in the following figure).

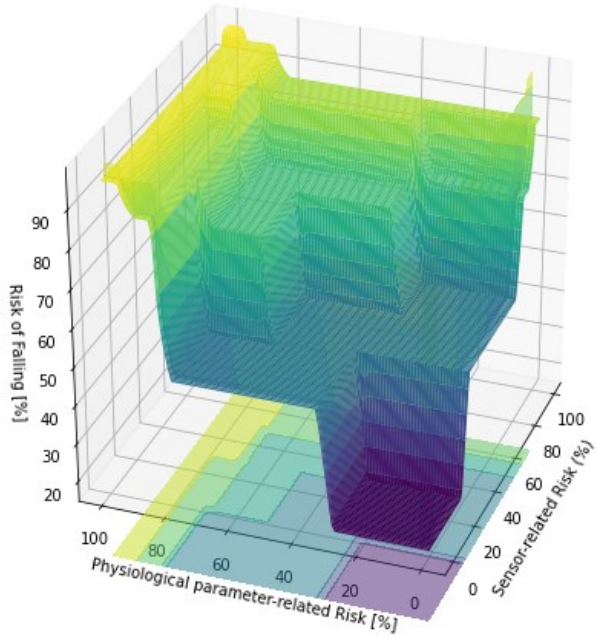

Figure 8: Fall-risk prediction represented here in 3D.

The outputs sets are reported below, the first one model the risk related to the information recorded by environmental sensors and its sets are divided into “very low”, “low”, “medium”, “high”, and “very high”. The second picture represents the membership function for the risk obtained from the physiological input values. These sets are described as input to define the final risk of falling, which has its membership function divided into 6 sets: “very low”, “low”, “medium”, “high”, “very high”, and “max”.

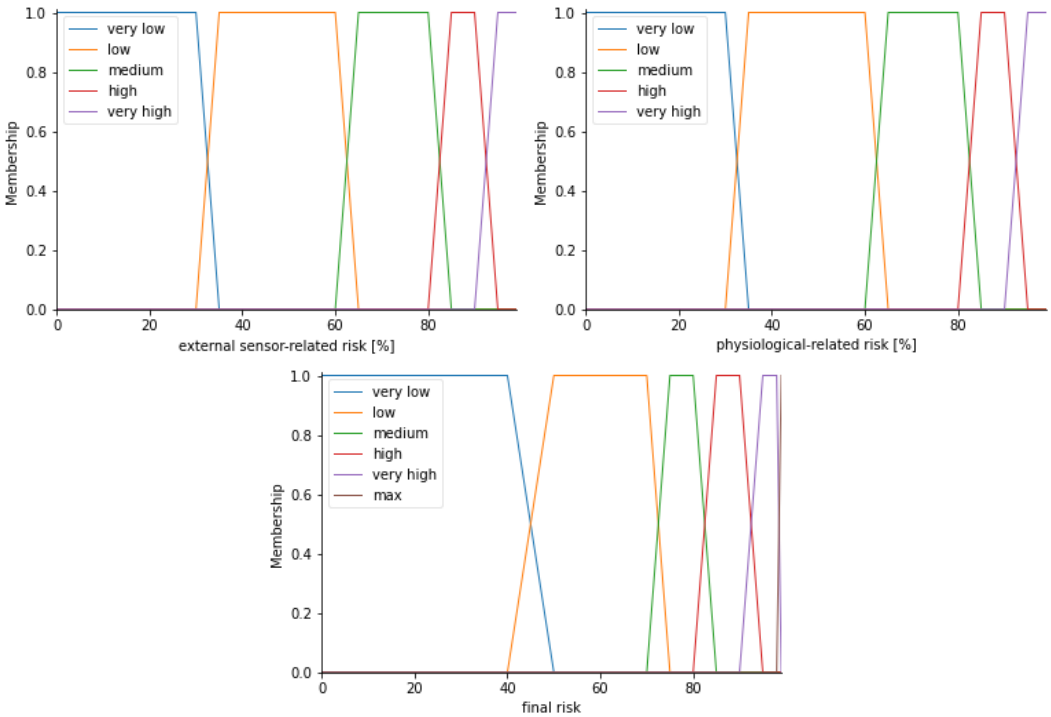

Figure 9: Membership functions for the risk related to the external sensors, the risk related to the physiological information, and the final risk of falling fuzzy sets.

3.3.3. Risk related to microclimate

The same representation is done for the evaluation of the risk related to microclimate represented in the following scheme. In this case the FIS is built with two different FIS as inputs: one with the information related to *temperature*, *humidity*, and *vocal noise*, and the other that considers physiological parameters (*COPD* and *Heart rate variation*).

Each input described is defined with the fuzzy sets reported below in figure 13. *Temperature* input is divided into 4 sets labelled “low”, “optimal”, “high”, and “very high”. The same subdivision is adopted for *humidity* input. *COPD* instead has 2 sets that represent the absence or presence of that respiratory disorder respectively. *Vocal noise* and *Heart rate variation* have the same membership function previously described in figure 9.

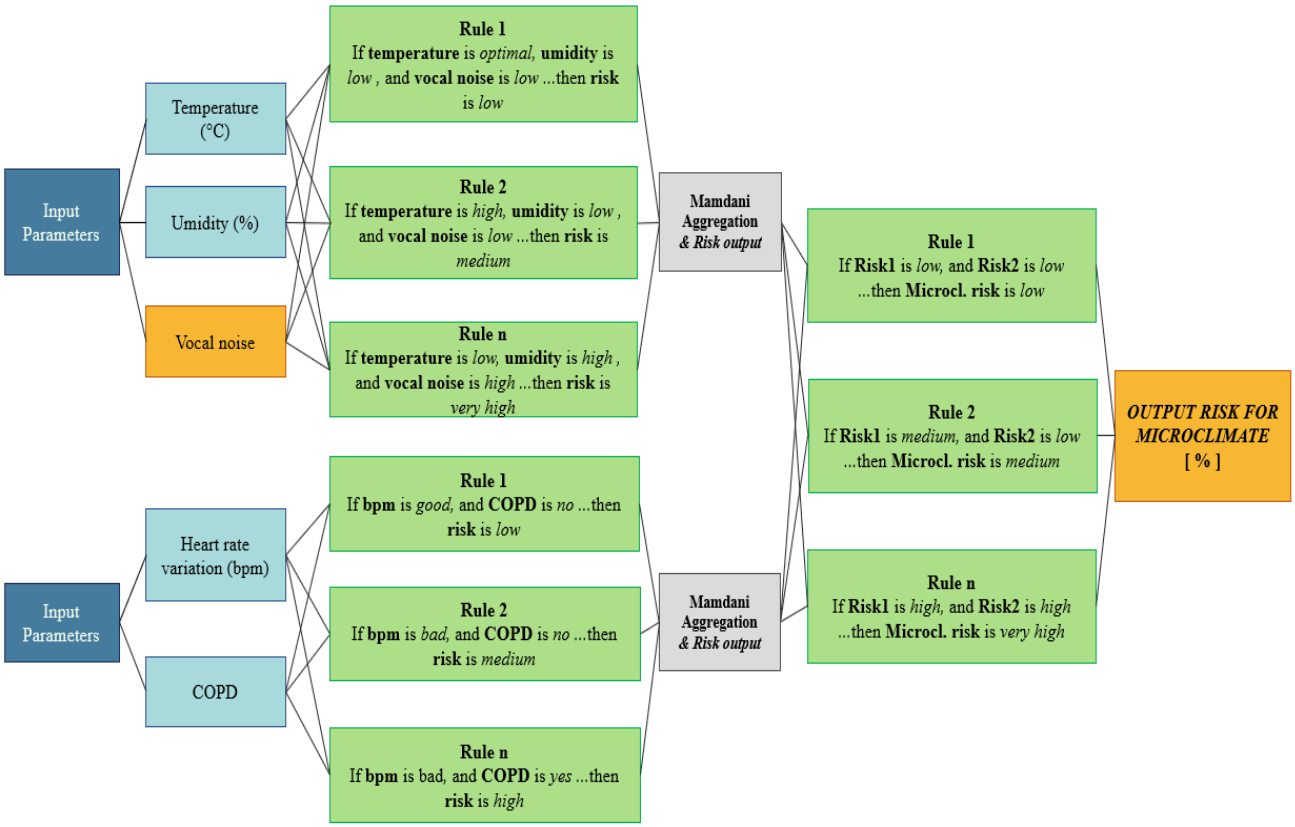

Figure 10: Block scheme of FISs for prediction of Risk related to microclimate conditions.

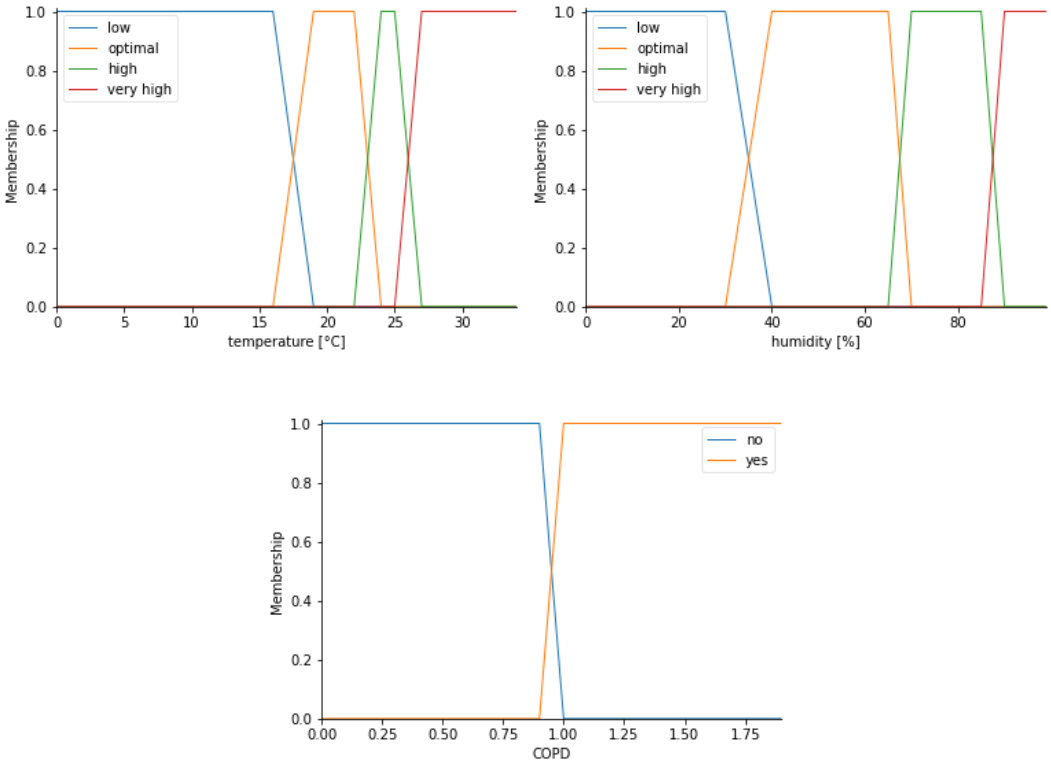

Figure 11: Membership functions which constitute temperature, humidity, and COPD.

The three-dimensional representation in this case seems to have higher percentage values for higher values of sensors inputs (so for variation in temperature or humidity for example) with respect to the other parameters. That assumption is discussed further in the results chapter. All the rules related to this risk assumption are reported in the *Appendix C*.

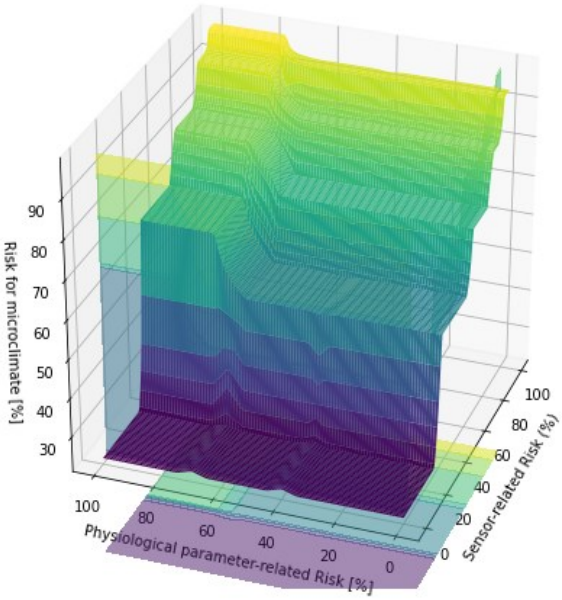

Figure 12: Ambient-related risk prediction represented here in 3D. The sensor-related risk axe represents the risk related to the external information and has a bigger weight in the evaluation of the final output.

Also in this case the outputs sets are reported below, the first one model the risk related to the information recorded by environmental sensors and its sets are divided into “very low”, “low”, “medium”, “high”, and “very high”. The second picture represents the membership function for the risk obtained from the physiological input values. In this case the physiological information have a lower weight in the definition of the risk related to microclimate and the fuzzy sets are just 3: “low, “medium”, and “high”. The final output related to the quality of the microclimate has the same fuzzy sets as the risk of falling.

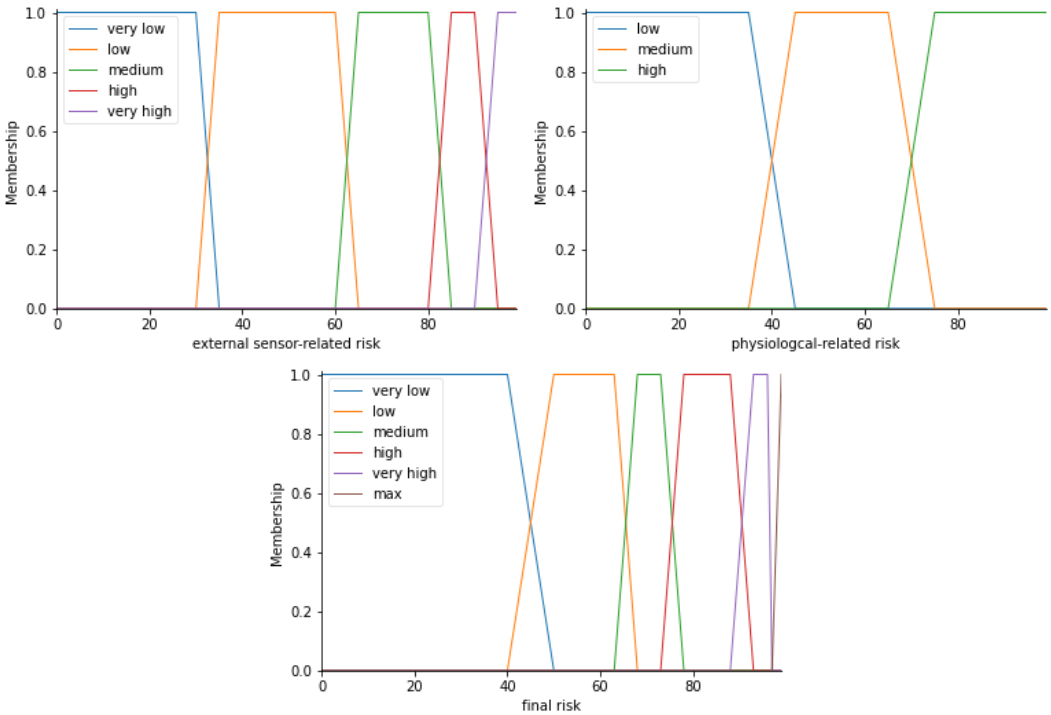

Figure 13: Membership function of the final risk related to the quality of the microclimate, which inputs are the external sensor related risk (left), and the physiological related risk (right).

3.3.4. Risk of Escaping

The escaping risk has four inputs: the presence/absence of dementia, vocal noise, bpm value and the duration of walking. In this case a single FIS is implemented in the way is showed in figure 14. In this case the main input to be considered is the presence of dementia, that is the key factor for the possibility that the subject may escape from the nursing home.

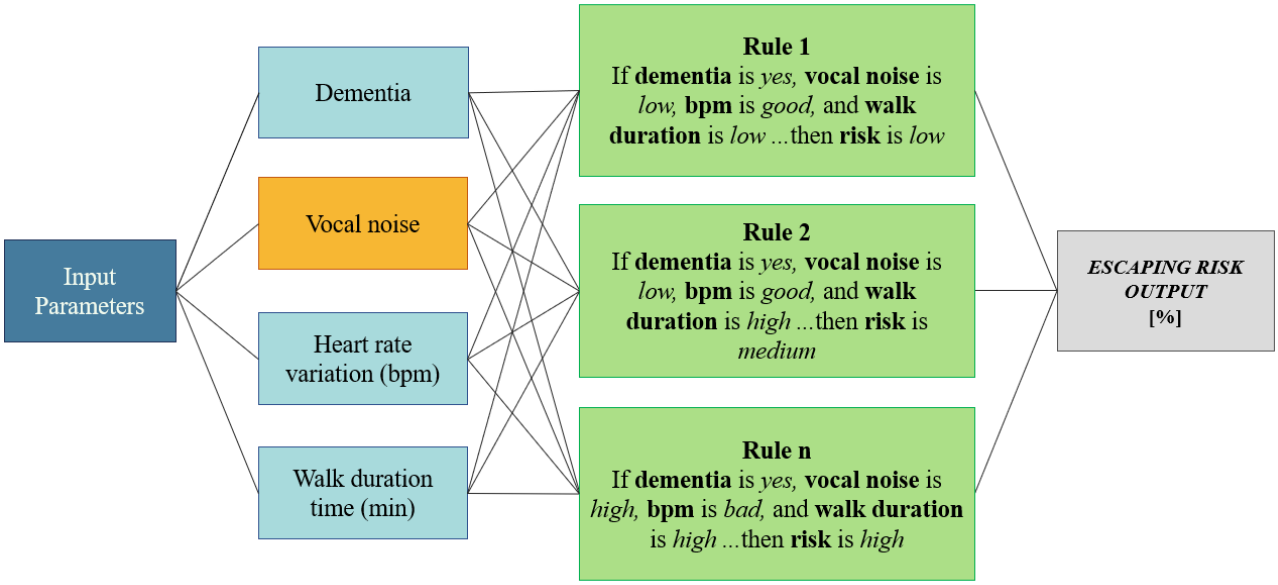

Figure 14: FIS for the evaluation of the risk of escaping.

The input values present in this FIS are previously described in figure 9, with exception for *Dementia*, which has a Boolean value. So, its membership function has the same structure that COPD has in figure 10. In this case the risk output is modelled with 4 fuzzy sets called "low", "medium", "high", and "very high". All the rules related to this risk are reported in the *Appendix D.*

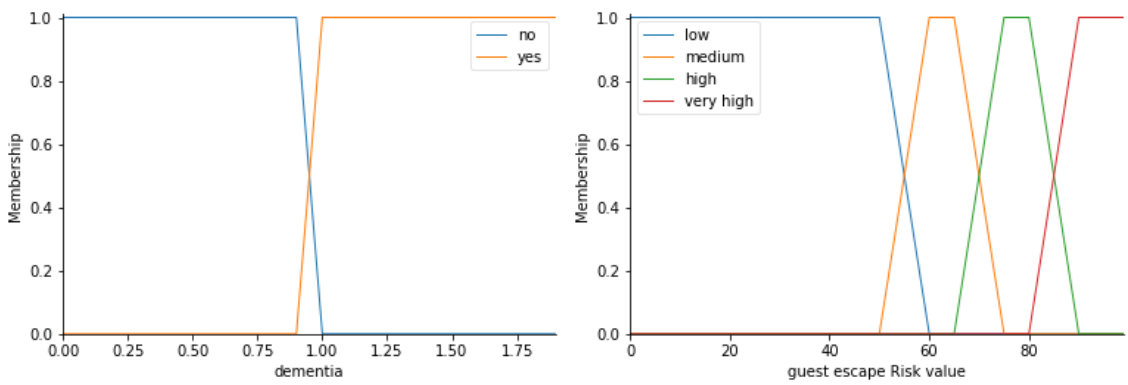

Figure 15: Membership function of Dementia, which has a Boolean value (0-1) (left). On the right there is the graphical representation of the output fuzzy sets for the risk of escaping. The other inputs are described in the other risk definitions.

All these assumptions are evaluated in the results section, where the percentages obtained with these systems for some specific cases are compared with the evaluation that some clinicians give with the same premises.

4. RESULTS AND DISCUSSION

After the information necessary to build the FISs were fixed, 2 questionnaires with values corresponding to different scenarios are given to 8 clinicians, and it was asked to them to define a percentage with which they would describe the occurrence of a specific risk under those circumstances. The first questionnaire they filled out contains the following questions related to the risk with FIS, and the clinician indicates the percentage of risk he retains correct between *very low risk* (0-30 %), *low risk* (30-50%), *medium* (60-75%), *high* (75-85%), *very high* (85-100%).
They try to estimate the risk of falling for the following situations:

1. *The guest gets out of bed 3 times during the night, wanders for at least 30 minutes each time and this occurs for more than 3 consecutive days.*
2. *The guest has very low blood pressure for at least 2 consecutive days.*
3. *The guest has high blood pressure for at least 2 consecutive days.*
4. *The guest appears agitated, with high heart rate than usual and nocturnal moans for 4 consecutive days.*
5. *What would the probability be if the combination of scenario 1 and 2 occurs? (night wandering + low blood pressure)*
6. *What would the probability be if the combination of scenarios 1 and 3 occurs? (night wandering + high blood pressure).*
7. *What would the probability be if the combination of scenarios 1 and 5 occurs? (night wandering + agitation state)*
8. *What would the probability be if the combination of scenarios 2 and 5 occurs? (low blood pressure + agitation state)*
9. *What would the probability be if the combination of scenarios 3 and 5 occurs? (high blood pressure + agitation state)*
10. *How would the probability be if the guest got up frequently every night, showing a state of agitation and with pressure values out of range recorded during the days.*

To estimate the risk related to the quality of the microclimate they evaluate the following scenario:

1. *In the guest room the temperature is > 22 °:*
2. *In the guest room the temperature is > 22 ° and the humidity exceeds 70%:*
3. *In the guest room the temperature is > 25 °:*
4. *In the guest room the temperature is > 25 ° and the humidity exceeds 70%:*
5. *In the guest room the temperature is < 15 °:*
6. *In the guest room the temperature is < 15 ° and the humidity exceeds 70%:*

7. *This case refers to condition 1, plus the guest shows a state of agitation.*
8. *This case refers to condition 2, plus the guest shows a state of agitation.*
9. *This case refers to condition 4, plus the guest shows a state of agitation.*
10. *This case refers to condition 5, plus the guest shows a state of agitation.*
11. *This case refers to condition 6, plus the guest shows a state of agitation*
12. *This case refers to condition 1, plus the host is suffering from COPD (Chronic Obstructive Pulmonary Disease).:*
13. *This case refers to condition 2, plus the host is suffering from COPD.*
14. *This case refers to condition 4, plus the host is suffering from COPD.*
15. *This case refers to condition 5, plus the host is suffering from COPD.*
16. *This case refers to condition 6, plus the host is suffering from COPD.*
17. *If the microclimate of the room is altered, the guest is affected by COPD and shows a state of agitation, what would be the percentage of risk?*

Finally, to estimate the risk of escaping the clinician's answer to these 3 questions:

1. *The guest is affected by dementia and he/she appears agitated (higher heart rate than usual, numerous and continuous complaints about at least 7 consecutive days):*
2. *The guest with dementia wandering inside the structure during the night, this fact is repeated for at least 3 consecutive days:*
3. *The guest shows a state of agitation and in addition, he/she wanders during the night (a combination of the previous cases).*

All these scenarios are investigated by both the FISs and the experts of the domain (that set up a score for the risk related to that conditions), to evaluate algorithm accuracy in the recognition of the level of gravity related to the risk.

The following tables report the input values and the corresponding outputs, as a percentage of risk. Together with the risks defined with the FISs, the 2nd questionnaire contains the following questions related to the other risks (without fuzzy logic), and the clinician indicates the percentage of risk he retains correct between these 3 options: "*no risk", "risk with medium probability", "risk with high probability"*.

All inferences are processed in parallel by the system, by considering the inputs received each day, and all the risks are computed simultaneously. The clinicians operate in the same way.

The questions they answered are reported below, and the columns on the right report the answers:

Table 1: List of questions to investigate risks. the last column presents the level with which the clinicians assume that risk will realize in the next future, while the previous column represents the same evaluation given by our system.

Risk Scenario	**Risk level**	**Risk level**

	System	Clinicians
Risk of the wrong assumption of medication.		
The patient therapy is prepared without following the updated indications of the guest's therapy card, it happens for 1 or 2 days.	**Low**	**Medium**
The therapy is prepared without following the updated indications of the guest's therapy card, it happens for 7 or + consecutive days.	**High**	**High**
Therapy for the scheduled time is administered to the guest several times or is not administered, it happens 1 or 2 consecutive days	**Low**	**Medium**
Therapy for the scheduled time is administered to the guest several times or is not administered, it happens 7 or + consecutive days	**High**	**High**
Suicide risk.		
In the multidimensional evaluation (VMD) of the host, recorded every 6 months, it appears that the guest suffers from depression, and often refuses assistance.	**Low**	**Medium**
It is recorded that the guest has not eaten or eats very little for 5 or + consecutive days.	**Low**	**Medium**
Combination of the two previous cases (depression + malnutrition for 5 or more consecutive days).	**High**	**High**
Risk related to lack of care procedures.		
Some activities provided for in the Guest's Individualized Service Plan (IPS) in Italian) scheduled for the day are not carried out, this occurs for 2 consecutive days.	**Medium**	**Medium**
A guest contracts an infection, and within about 20 days the same infection is found in other guests of the facility. What is the probability that some operators perform the activities in the wrong way?	**High**	**High**
Risk of malnutrition.		
It is recorded that the guest has not eaten or eats very little for 5 or + consecutive days.	**Medium**	**Medium**
It is noted that the weight of a guest of the facility has increased or decreased by 3% in just 30 days.	**Medium**	**Medium**
Combination of these two cases: It is noted that the weight of a guest in the facility decreased by 3% in just 30 days, plus the guest has not been eating or eats little for at least 5 days.	**High**	**High**
Risk of aspiration pneumonia.		
It is recorded that the guest coughs repeatedly during the night, for a minimum of 30 minutes.	**Medium**	**Medium**
In the Multidimensional evaluation of the patient, it appears that he/she suffers from dysphagia.	**Low**	**Medium**
Combination of the previous two (dysphagia + repeated cough).	**High**	**High**
In the Multidimensional evaluation of the patient, it appears that he/she suffers from Parkinson.	**Low**	**Low**
Combination of the previous two (Parkinson + repeated cough).	**High**	**High**
Risk of injury due to a fight between residents.		
Information from the multidimensional evaluation shows that the guest is violent.	**Low**	**Medium**
From the VMD the guest is violent + the guest shows signs of agitation in the last few days.	**High**	**High**

Risk of injuries due to pressure sores		
The guest's care plan provides for it to be mobilized, but this activity is skipped for 1 day.	**Low**	**Low**
The guest's care plan provides for it to be mobilized, but this activity is skipped for 4 or more days.	**High**	**Medium**
The guest in question is in a coma and is not mobilized for 1 day.	**Medium**	**Medium**
The guest in question is in a coma and is not mobilized for 4 or more days.	**High**	**High**

In some cases, here we can observe that the clinicians evaluate risk conditions with a greater risk percentage with respect to the system. This aspect could involve the fact that they make assumptions based on their personal knowledge of the condition of a patient when he/she is subjected to a specific disease. However, the system is built in a way that it will trigger the alarm just in case of some changes in the health condition of the guest. For example, considering the risk of aspiration pneumonia, if the VMD of the subject reports that he suffers from dysphagia, this information is stored in the database for months. So, if the system recognizes this information sufficient to trigger the alarm, the risk of aspiration pneumonia will be on every day for this subject, which makes it useless for the operators to detect just the occurrence of the risk event. The same procedure is adopted for the risk of injury due to a fight between residents, or for the risk of suicide. The following table corresponds to the evaluation of the percentage of risk of falling base on the questions previously defined. The evaluation of the range the 8 clinicians defined is reported as a mean value calculated from their assumptions.

Table 2: Each row represent an example case, with the values corresponding to the mean between the days under examination (defined in chapter 3.2 for each parameter).the last 2 columns correspond to the percentage of the risk of falling obtained with the FIS and by the evaluation of the clinicians respectively.

N° of ups	V. Noise intensity [dB]	V. Noise duration [min]	Walking time [min]	Heart rate diff.	Systolic pressure [mmHg]	Future risk of falling	Clinician prediction risk of falling	Absolute error (Δe)
3	-	-	40	-	125	**77 %**	**80%**	3 %
-	-	-	-	-	105	**87 %**	**85%**	2 %
-	-	-	-	-	170	**77 %**	**68 %**	9 %
-	55	40	-	50	125	**59 %**	**65 %**	6 %
3	-	-	40	-	105	**95 %**	**95 %**	0 %
3	-	-	40	-	170	**80 %**	**80 %**	0 %
3	55	40	40	50	125	**87 %**	**85 %**	2 %
-	55	40	-	50	105	**95 %**	**90 %**	5 %
-	55	40	-	50	170	**77 %**	**68 %**	9 %
3	55	40	40	50	105	**99 %**	**95 %**	4 %

As it is possible to see in the *"clinicians' prediction"* column, for each scenario a particular range of values is identified by comparing all the answers from the experts. Also, it is possible to see that the system results belong quite well inside most of all these ranges, as a result, that this FIS works well in predicting the gravity of the risk of falling since the error values are relatively small with an exception for just a couple of scenarios. The error reported here is the absolute value of the difference between the percentage obtained by the FIS and the value from the clinicians. Both the clinicians and the system identify the higher risk of falling in the presence of low pressure in the patient. In fact, for a scenario where a blood pressure level lower than 120 mmHg for two consecutive days is detected, the risk of falling reaches a percentage of 87% by just considering this parameter itself. If we assume that, for example, the same subject is also wondering during the night, then the risk of falling that the system predicts rises at 95%. The maximum value for the risk percentage is related to the presence of all the input values together that shows up a 99% risk of falling. Note that each input needs to happen for a different number of days consequently with respect to the other: the night walks have to repeat for 3 days with a high value to represent an input for the FIS, while for the blood pressure two days are enough. The agitation state instead must occur every day for an entire week to be considered. That allows the system to recognize a risk of falling before much time passes and set the proper alarm to the operators. In this way, those are informed and can keep an eye on the situation before it is too late.

Table 3 follows the same structure previously described to define the risk related to the microclimate.

Table 3: Each row represent an example case, with the values corresponding to the mean between the days under examination (defined in chapter 3.2 for each parameter).the last 2 columns correspond to the percentage of the health risk related to the quality of microclimate obtained with the FIS and with the evaluation of the clinicians respectively.

Temperature [°C]	Humidity [%]	V. Noise intensity [dB]	V. Noise duration [min]	Heart rate diff.	COPD	Future health risk for microclimate	Clinician prediction risk for microclimate	Absolute error (Δe)
23	40	-	-	-	NO	**55 %**	**57 %**	2%
23	80	-	-	-	NO	**70 %**	**75 %**	5%
27	40	-	-	-	NO	**83 %**	**80 %**	3%
27	80	-	-	-	NO	**83 %**	**85 %**	2%
13	40	-	-	-	NO	**83 %**	**80 %**	3%
13	80	-	-	-	NO	**83 %**	**80 %**	3%
23	40	55	40	50	NO	**70 %**	**70 %**	0%
23	80	55	40	50	NO	**83 %**	**80 %**	3%
27	80	55	40	50	NO	**95 %**	**95 %**	0%
13	40	55	40	50	NO	**83 %**	**80 %**	3%
13	80	55	40	50	NO	**93 %**	**85 %**	8%
23	40	-	-	-	YES	**70 %**	**75 %**	5%

23	80	-	-	-	YES	**83 %**	**80 %**	3%
27	80	-	-	-	YES	**93 %**	**95 %**	2%
13	40	-	-	-	YES	**93 %**	**85 %**	8%
13	80	-	-	-	YES	**93 %**	**85 %**	8%
13	80	55	40	50	YES	**98 %**	**95 %**	3%

By looking at table 3 last columns, the outputs of the FIS are close with the percentages described by the clinicians. The higher risk values belong to situations where the patient suffers from *COPD* (Chronic Obstructive Pulmonary Disease) or when the patient seems agitated. The most important input to consider is the variation of temperature out of range, which influences most the evaluation of the risk related to the microclimate. The higher risk values correspond to very high (above 25°) or very low (under 18°) temperatures, which show a risk value of 83% by themselves. There is also a difference in risk percentage related to the humidity input value given by the clinicians, but since the difference in percentage seems small the system output fits the percentage ranges in both cases with the same result. The highest value of risk for microclimate obtained here by the FIS is 98% when all the inputs are present together. Also, in this system, some scenarios have outputs out of range, but the variation seems negligible. Plus, that happens for situations where a subject affected by COPD belongs in a room with a low temperature. The results given by the clinicians, in this case, have different values, so even if the final range results around 85%, it is better to give a higher percentage risk alarm (93 % from the FIS) to the operator in a way that they will intervene faster.

The last risk present in this project is the risk of escaping, which has a smaller number of parameters to consider to be evaluated. The following table reports three examples of different situations.

Table 4: Each row represent an example case, with the values corresponding to the mean between the days under examination (defined in chapter 3.2 for each parameter).the last 2 columns correspond to the percentage for the escaping risk evaluated with the FIS and with clinicians evaluation respectively.

Dementia	V. Noise intensity [dB]	V. Noise duration [min]	Bpm diff.	Walking time [min]	Future risk of escaping	Clinician prediction risk of escaping	Absolute error (Δe)
YES	50	40	50	-	**63 %**	**67 %**	4%
YES	-	-	-	40	**77 %**	**75 %**	2%
YES	50	40	50	40	**92 %**	**90 %**	2%

The key input here is that the subject must be affected by dementia. As previously said (in chapter 3.2.9) the presence of the other two input values does not constitute a risk factor individually, but the simultaneous presence of the cases listed above with these latter increases risk probability. The fact that he/she keeps walking (especially during nights) shows a higher risk of escaping (77%) with respect to the case where he seems just agitated (63%). The highest value corresponds to the presence of both the wondering and the agitation state in the patient affected by dementia.

The following table presents the mean error of each fuzzy inference system, with its standard deviation. The mean error is calculated as a sum of all the absolute errors for each test data, divided by the number of tests. It is reported together with its standard deviation, calculated in this way:

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2}$$

Where N is the number of data, x_i the absolute error for each data, and x the mean error. The obtained values are:

Table 5: Mean error and its standard deviation for the risk evaluated with the FISs.

	Mean error (m)	**Standard deviation error (s)**
Risk of falling	4%	3.3
Risk related to quality of microclimate	3.6%	2.5
Risk of escaping	2.7%	1.1

By looking at these values, all the FIS have a range of error that is relatively small. The risk of escaping seems the one with the best results. However, it is also the risk with the FIS that has inputs with very specific values (like the fact that dementia must be present), and so a few numbers of scenarios were investigated. The risk related to the quality of microclimate, instead, has 17 different scenarios tested with the help of the clinicians, and its model has a good error with a small standard deviation. In this case, we can assume that the higher accuracy with which the system predicts the risk percentage with respect to the risk of falling is based on the higher weight well specified that some inputs (temperature and humidity in this case) have in defining risk output. If we observe the plots below, they point out how the judgment of the experts is consistent with the algorithm scores, with a better evaluation in the cases where FIS is implemented.

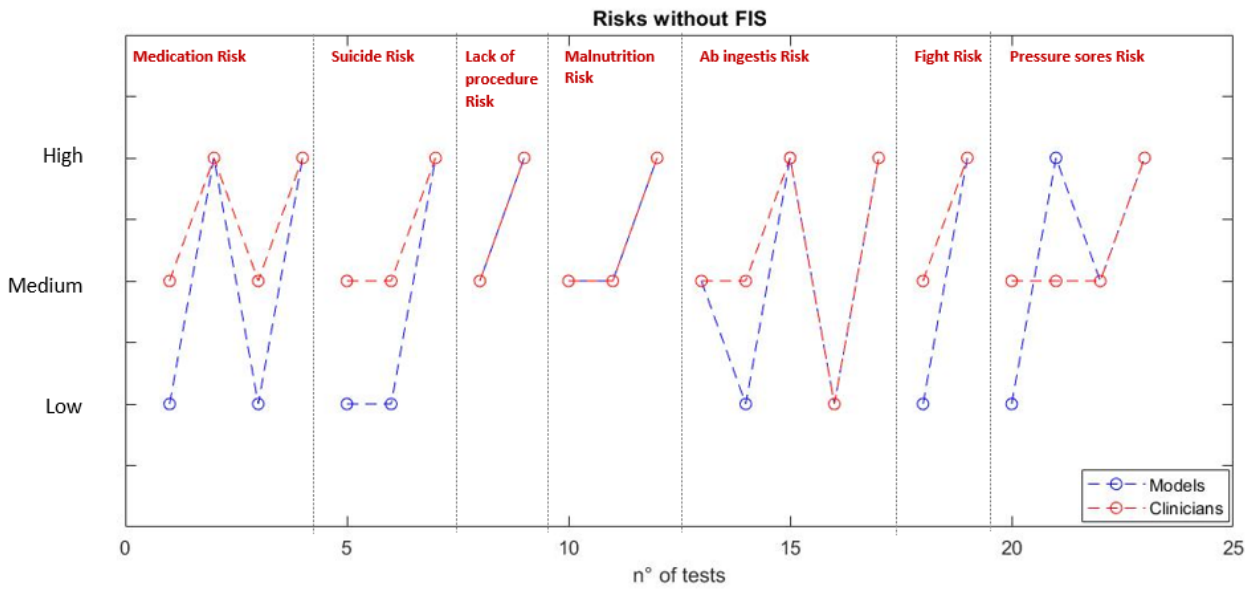

Figure 16: Scores obtained for the risks without fuzzy system (blue) with respect to clinicians' evaluation (red).

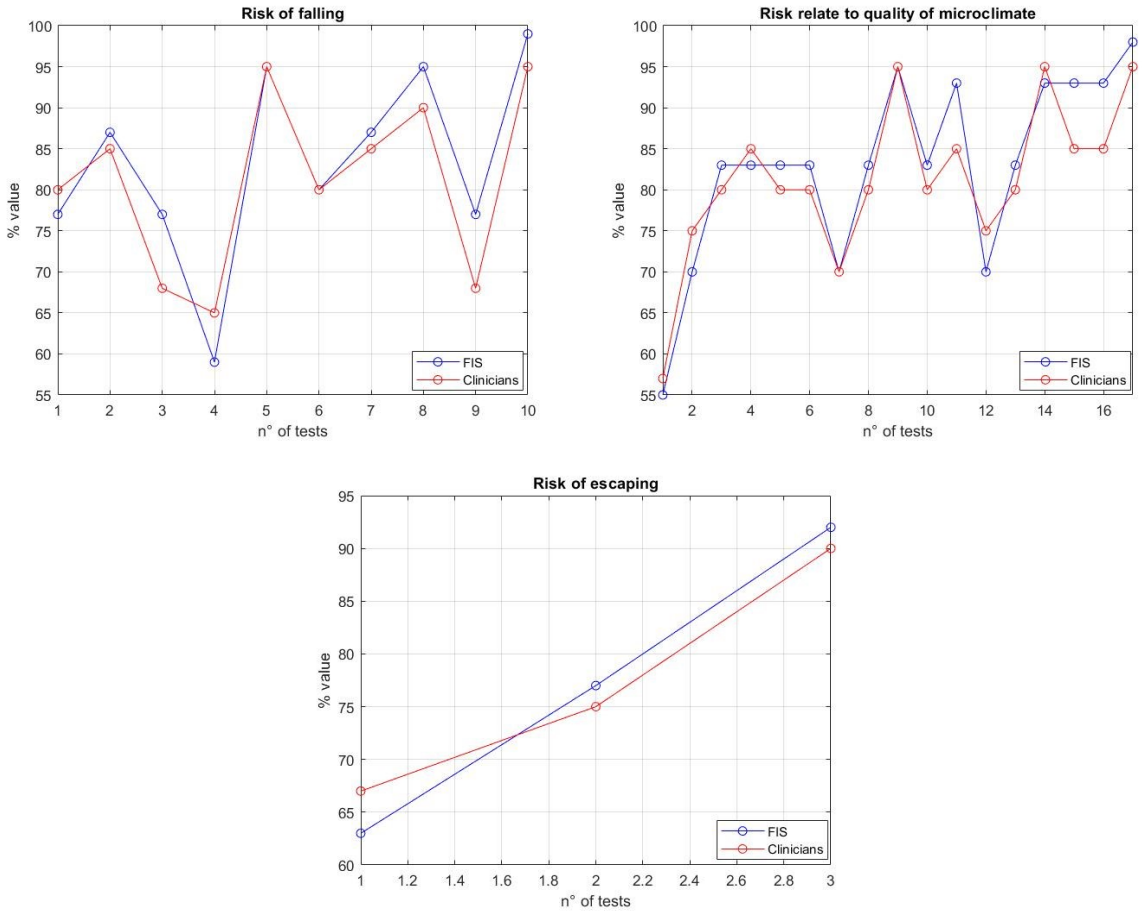

Figure 17: Percentage scores obtained from the FIS model (in blue) and the clinicians (red) evaluation.

The purpose of this project is an overall decision support system, a total expert system is set up with information retrieval through interviews of experts. The whole system represents an important step up for a structure like a nursing home, where a few numbers operators handle many patients at the same time. There are a lot of events or accidents that could happen, and nobody will notice it, or maybe do it when it is too late since old people are more fragile with respect to other people. Just the fact that the technology will record everything around him during each day will help to provide the correct information any time, during a nurse's shift change for example.

The implementation of a fuzzy inference system was chosen after different considerations: the first one is the absence of a previous database. A massive amount of data is needed to obtain a classification approach with a good level of accuracy. Even if there are a lot of researches about old people monitoring and lifestyle prediction, most of them are conducted only on a single specific task, and most importantly dataset related to health condition are subjected on privacy, so they are not accessible most of the times. Another critical factor to consider about why a FIS is applied here is that it is based on systematic observation and on the verification of factors that influence the result. Especially in this case is better not to use a "black box" type of decision model, but a

transparent tool that can be updated with new knowledge. Plus, the linguistic variable is extremely useful in such cases, to deal with situations that are not well defined that need to be expressed quantitatively. For these reasons an expert system approach in this field is the best performing. The obtained results also demonstrate the capacity of the FIS to put together various kind of knowledge and decode it in a way like a clinician's way of thinking.

This initial implementation of these models all together demonstrates the potential of the architecture and will serve as a very important testbed for future work.

5. APPENDIX

This chapter contains all the rule base generated, according to the logic of inference, in which the "and" connector is represented by &. Antecedent and consequent are obtained by the Python function *ctrl.Rule(Antecedent, Consequent,..)* where ctrl indicates the sub package *Control* contained in *scikitFuzzy* library.

Appendix A

From the 2 input variables (*intensity and time duration*), 6 rules are generated to define the vocal noise score:

1. intensity['low'] & duration['low'], *then* vnoise['low']
2. intensity['medium'] & duration['low'], *then* vnoise['low']
3. intensity['low'] & duration['high'], *then* vnoise['medium']
4. intensity['high'] & duration['low'], *then* vnoise['medium']
5. intensity['medium'] & duration['high'], *then* vnoise['high']
6. intensity['high'] & duration['high'], *then* vnoise['high']

Appendix B

From the first 3 input variables related to the environment information (*n° of ups, vocal noise and night walking duration*), 18 rules are defined:

1. up['low'] & vnoise ['low'] & steptime['low'], *then* risk['very low']
2. up['low'] & vnoise ['low'] & steptime['high'], *then* risk['low']
3. up['medium'] & vnoise ['low'] & steptime['low'], *then* risk['low']
4. up['low'] & vnoise ['medium'] & steptime['low'], *then* risk['low']
5. up['low'] & vnoise ['high'] & steptime['low'], *then* risk['low']
6. up['medium'] & vnoise ['low'] & steptime['high'], *then* risk['medium']
7. up['high'] & vnoise ['low'] & steptime['low'], *then* risk['medium']
8. up['low'] & vnoise ['medium'] & steptime['high'], *then* risk['medium']
9. up['medium'] & vnoise ['medium'] & steptime['low'], *then* risk['medium']
10. up['medium'] & vnoise ['high'] & steptime['low'], *then* risk['medium']
11. up['low'] & vnoise ['high'] & steptime['high'], *then* risk['medium']

12. up['high'] & vnoise ['low'] & steptime['high'], *then* risk['high']
13. up['medium'] & vnoise ['medium'] & steptime['high'], *then* risk['high']
14. up['high'] & vnoise ['medium'] & steptime['low'], *then* risk['high']
15. up['medium'] & vnoise ['high'] & steptime['high'], *then* risk['high']
16. up['high'] & vnoyse ['high'] & steptime['low'], *then* risk['high']
17. up['high'] & vnoise ['medium'] & steptime['high'], *then* risk['very high']
18. up['high'] & vnoise ['high'] & steptime['high'], *then* risk['very high']

From physiological information (*heart rate variation and blood pressure*) other 8 rules are defined:

1. bpm['good'] & s_pres['normal'], *then* risk['very low']
2. bpm['bad'] & s_pres['normal'], *then* risk['low']
3. bpm['good'] & s_pres['high'], *then* risk['medium']
4. bpm['good'] & s_pres['very high'], *then* risk['medium']
5. bpm['bad'] & s_pres['high'], *then* risk['medium']
6. bpm['bad'] & s_pres['very high'], *then* risk['medium']
7. bpm['good'] & s_pres['low'], *then* risk['high']
8. bpm['bad'] & s_pres['low'], *then* risk['very high']

The outputs of these 2 FISs (called *Risk1* and *Risk2*) are combined to obtain the final risk of falling (*Rtot*) with the following 25 rules:

1. Risk1['very low'] & Risk2['very low'], *then* Rtot['very low']
2. Risk1['low'] & Risk2['very low'], *then* Rtot['low']
3. Risk1['very low'] & Risk2['low'], *then* Rtot['low']
4. Risk1['low'] & Risk2['low'], *then* Rtot['low']
5. Risk1[high'] & Risk2['very low'], *then* Rtot['medium']
6. Risk1['medium'] & Risk2['low'], *then* Rtot['medium']
7. Risk1['low'] & Risk2['medium'], *then* Rtot['medium']
8. Risk1['medium'] & Risk2['medium'], *then* Rtot['medium']
9. Risk1['very low'] & Risk2['medium'], *then* Rtot['medium']
10. Risk1['medium'] & Risk2['very low'], *then* Rtot['medium']
11. Risk1['very high'] & Risk2['very low '], *then* Rtot['high']

12. Risk1['high'] & Risk2['low '], *then* Rtot['high']
13. Risk1['very high'] & Risk2['low '], *then* Rtot['high']
14. Risk1['very high'] & Risk2['medium '], *then* Rtot['high']
15. Risk1['very low'] & Risk2['high '], *then* Rtot['high']
16. Risk1['high'] & Risk2['medium'], *then* Rtot['high']
17. Risk1['low'] & Risk2['high '], *then* Rtot['very high']
18. Risk1['medium'] & Risk2['high '], *then* Rtot['very high']
19. Risk1['medium'] & Risk2['very high '], *then* Rtot['very high']
20. Risk1['low'] & Risk2['very high '], *then* Rtot['very high']
21. Risk1['very low'] & Risk2['very high '], *then* Rtot['very high']
22. Risk1['high'] & Risk2['high '], *then* Rtot['very high']
23. Risk1['very high'] & Risk2['high '], *then* Rtot['very high']
24. Risk1['high'] & Risk2['very high '], *then* Rtot['very high']
25. Risk1['very high'] & Risk2['very high '], *then* Rtot['max']

Appendix C

From the first 3 input variables (*temperature, humidity, and vocal noise*) related to the environment information, 48 rules are defined:

1. temp['optimal'] & umi['optimal'] & vnoise['low'], *then* risk['very low']
2. temp['optimal'] & umi['optimal'] & vnoise['medium'], *then* risk['very low']
3. temp['optimal'] & umi['optimal'] & vnoise['high'], *then* risk['very low']
4. temp['optimal'] & umi['low'] & vnoise['low'], *then* risk['low']
5. temp['optimal'] & umi['low'] & vnoise['medium'], *then* risk['low']
6. temp['optimal'] & umi['high'] & vnoise['low'], *then* risk['low']
7. temp['optimal'] & umi['high'] & vnoise['medium'], *then* risk['low']
8. temp['high'] & umi['optimal'] & vnoise['low'], *then* risk['low']
9. temp['high'] & umi['optimal'] & vnoise['medium'], *then* risk['low']
10. temp['optimal'] & umi['low'] & vnoise['high'], *then* risk['medium']
11. temp['optimal'] & umi['high'] & vnoise['high'], *then* risk['medium']
12. temp['optimal'] & umi['very high'] & vnoise['high'], *then* risk['medium']

13. temp['high'] & umi['low'] & vnoise[‘low’], *then* risk['medium']
14. temp['high'] & umi['low'] & vnoise[‘medium’], *then* risk['medium']
15. temp['high'] & umi['optimal'] & vnoise[‘high’], *then* risk['medium']
16. temp['high'] & umi['high'] & vnoise[‘low’], *then* risk['medium']
17. temp['high'] & umi['high'] & vnoise[‘medium’], *then* risk['medium']
18. temp['low'] & umi['low'] & vnoise[‘low’], *then* risk['high']
19. temp['low'] & umi['low'] & vnoise[‘medium’], *then* risk['high']
20. temp['low'] & umi['optimal'] & vnoise[‘low’], *then* risk['high']
21. temp['low'] & umi['optimal'] & vnoise[‘medium’], *then* risk['high']
22. temp['low'] & umi['low'] & vnoise[‘high’], *then* risk['high']
23. temp['low'] & umi['optimal'] & vnoise[‘high’], *then* risk['high']
24. temp['low'] & umi['high'] & vnoise[‘low’], *then* risk['high']
25. temp['low'] & umi['high'] & vnoise[‘medium’], *then* risk['high']
26. temp['low'] & umi['very high'] & vnoise[‘low’], *then* risk['high']
27. temp['low'] & umi['very high'] & vnoise[‘medium’], *then* risk['high']
28. temp['optimal'] & umi['very high'] & vnoise[‘high’], *then* risk['high']
29. temp['high'] & umi['low'] & vnoise[‘high’], *then* risk['high']
30. temp['high'] & umi['high'] & vnoise[‘high’], *then* risk['high']
31. temp['high'] & umi['very high'] & vnoise[‘low’], *then* risk['high']
32. temp['high'] & umi['very high'] & vnoise[‘medium’], *then* risk['high']
33. temp['very high'] & umi['low'] & vnoise[‘low’], *then* risk['high']
34. temp['very high'] & umi['low'] & vnoise[‘medium’], *then* risk['high']
35. temp['very high'] & umi['optimal'] & vnoise[‘high’], *then* risk['high']
36. temp['very high'] & umi['high'] & vnoise[‘low’], *then* risk['high']
37. temp['very high'] & umi['high'] & vnoise[‘medium’], *then* risk['high']
38. temp['very high'] & umi['very high'] & vnoise[‘low’], *then* risk['high']
39. temp['very high'] & umi['very high'] & vnoise[‘medium’], *then* risk['high']
40. temp['very high'] & umi['optimal'] & vnoise[‘low’], *then* risk['high']
41. temp['very high'] & umi['optimal'] & vnoise[‘medium’], *then* risk['high']

42. temp['very high'] & umi['very high'] & vnoise[‘medium’], *then* risk['very high']
43. temp['low’] & umi['high'] & vnoise[‘high’], *then* risk['very high']
44. temp[‘low’] & umi['very high'] & vnoise[‘high’], *then* risk['very high']
45. temp['high'] & umi['very high'] & vnoise[‘high’], *then* risk['very high']
46. temp['very high'] & umi['low'] & vnoise[‘high’], *then* risk['very high']
47. temp['very high'] & umi['high'] & vnoise[‘high’], *then* risk['very high']
48. temp['very high'] & umi['very high'] & vnoise[‘high’], *then* risk['very high']

From physiological information (*presence of COPD, and heart rate variation*) other 4 rules are defined:

1. bpm['good'] & BPCO['no'], *then* risk[‘low’]
2. bpm['bad'] & BPCO['no'], *then* risk[‘medium’]
3. bpm['good'] & BPCO['yes'], *then* risk[‘high’]
4. bpm['bad'] & BPCO['yes'], *then* risk[‘high’]

The outputs of these 2 FISs (called *Risk1* and *Risk2*) are combined to obtain the final risk related to the quality of microclimate (*Rtot*) with the following 15 rules:

1. Risk1['very low'] & Risk2['low'], *then* Rtot['very low']
2. Risk1['very low'] & Risk2['medium'], *then* Rtot['very low']
3. Risk1['very low'] & Risk2['high'], *then* Rtot['very low']
4. Risk1['low'] & Risk2['low'], *then* Rtot['low']
5. Risk1['low'] & Risk2['medium'], *then* Rtot['low']
6. Risk1['low'] & Risk2['high'], *then* Rtot['medium']
7. Risk1['medium'] & Risk2['low'], *then* Rtot['medium']
8. Risk1['medium'] & Risk2['medium'], *then* Rtot['medium']
9. Risk1['medium'] & Risk2['high'], *then* Rtot['high']
10. Risk1[‘high'] & Risk2['low'], *then* Rtot[‘high']
11. Risk1[‘high'] & Risk2['medium'], *then* Rtot[‘high']
12. Risk1[‘high'] & Risk2['high'], *then* Rtot[‘very high']
13. Risk1[‘very high'] & Risk2['low'], *then* Rtot[‘very high']
14. Risk1[‘very high'] & Risk2['medium'], *then* Rtot[‘very high']

15. Risk1[‘very high'] & Risk2['high'], *then* Rtot[‘max']

Appendix D

From the 4 input variables related to the risk of escaping, 24 total rules are defined:

1. dem['yes'] & bpm['good'] & vnoise['low'] & steptime['low'], *then* risk[‘low’]
2. dem['yes'] & bpm['good'] & vnoise['medium'] & steptime['low'], *then* risk[‘low’]
3. dem['no'] & bpm['good'] & vnoise['low'] & steptime['low'], *then* risk[‘low’]
4. dem['no'] & bpm['good'] & vnoise['medium'] & steptime['low'], *then* risk[‘low’]
5. dem['no'] & bpm['good'] & vnoise['low'] & steptime['high'], *then* risk[‘low’]
6. dem['no'] & bpm['good'] & vnoise['medium'] & steptime['high'], *then* risk[‘low’]
7. dem['no'] & bpm['good'] & vnoise['high'] & steptime['low'], *then* risk[‘low’]
8. dem['no'] & bpm['good'] & vnoise['high'] & steptime['high'], *then* risk[‘low’]
9. dem['no'] & bpm['bad'] & vnoise['low'] & steptime['low'], *then* risk[‘low’]
10. dem['no'] & bpm['bad'] & vnoise['medium'] & steptime['low'], *then* risk[‘low’]
11. dem['no'] & bpm['bad'] & vnoise['low'] & steptime['high'], *then* risk[‘low’]
12. dem['no'] & bpm['bad'] & vnoise['medium'] & steptime['high'], *then* risk[‘low’]
13. dem['no'] & bpm['bad'] & vnoise['high'] & steptime['low'], *then* risk[‘low’]
14. dem['no'] & bpm['bad'] & vnoise['high'] & steptime['high'], *then* risk[‘low’]
15. dem['yes'] & bpm['good'] & vnoise['high'] & steptime['low'], *then* risk[‘medium’]
16. dem['yes'] & bpm['bad'] & vnoise['low'] & steptime['low'], *then* risk[‘medium’]
17. dem['yes'] & bpm['bad'] & vnoise['medium'] & steptime['low'], *then* risk[‘medium’]
18. dem['yes'] & bpm['bad'] & vnoise['high'] & steptime['low'], *then* risk[‘medium’]
19. dem['yes'] & bpm['good'] & vnoise['low'] & steptime['high'], *then* risk[‘high’]
20. dem['yes'] & bpm['good'] & vnoise['medium'] & steptime['high'], *then* risk[‘high’]
21. dem['yes'] & bpm['good'] & vnoise['high'] & steptime['high'], *then* risk[‘very high’]
22. dem['yes'] & bpm['bad'] & vnoise['low'] & steptime['high'], *then* risk[‘very high’]
23. dem['yes'] & bpm['bad'] & vnoise['medium'] & steptime['high'], *then* risk[‘very high’]
24. dem['yes'] & bpm['bad'] & vnoise['high'] & steptime['high'], *then* risk[‘very high’]

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