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Agent Based Modelling for Simulating the Interregional Patient Mobility in Italy

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Abstract. Patient mobility is considered one of the main concerns for policy-makers as it impacts financial sustainability of regional health systems due to the high percentage of patients accessing care services in other regions. For a better understanding of this phenomenon, it is necessary to define a behavioral model able to represent the patient-system interaction. In this paper we adopted the Agent-Based Modelling (ABM) approach with the aim of simulating patient flow across regions and determining which are the main factors influencing it. This may provide a new insight for policy makers to capture which are the main factors influencing mobility and actions that may contribute to contain this phenomenon.

Keywords. Patient mobility, Agent-Based Modelling, Italy, Spatial accessibility, Simulation process

1. Introduction

Patient mobility studies the migration of patients to access to health services located outside his/her region of residence. It is considered as a proxy to appraise the quality and availability of hospital services [1] and to point out socio-economic disparities at local and regional level [2]. Different studies have underlined the main factors influencing this phenomenon [1], such as demographic and socio-economic status [3], quality and complexity of local services [4], structural components [5]. Among structural factors two inter-related aspects affect patient mobility: accessibility and availability of intra- and inter-regional facilities in particular for patients living at the regional borders [6]. In Italy, mitigating passive mobility is one of the main actions at the basis of the Health Pact 2019–2021 signed by the Conference of Regions and Autonomous Provinces [7]. This Health Pact highlights the necessity of mapping patient flows and drawing up a "plan to stop" passive mobility, with particular attention on critical care [1]. To further understand this phenomenon and capture which are the

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main factors influencing patient's choice, it is necessary to define a behavioral model that includes a variety of individual, community and socio-economic characteristics that represent the patient-system interaction. In different complex settings among which healthcare, this is done using Agent-Based Modelling (ABM) approach [8]. ABM is able not only to synthesize prior knowledge of a population and effectively represent and simulate this interaction [9], but also to understand how an intervention could modify the dynamics of patient behavior and affect public health [10]. Within this context, aim of this study is to design and propose an ABM approach for simulating patient flow across the Italian regions and determining which are the main factors influencing it. The suitability of this approach in this specific setting is tested considering both the accuracy and precision of the simulation process. The application of a robust ABM allows to define a mathematical model describing patient flow at an abstract level (i.e., region) and apply it to simulate the patient's behavior at a refined level (i.e., municipality). Moreover, this approach may provide a new insight for policy makers to capture which are the main factors influencing inter-regional patient mobility and to identify and put in place actions that may contribute to contain this phenomenon.

2. Materials and Methods

2.1. Data collection and identification of factors

Data on hospitals and mobility were gathered from the Ministry of Health website [11] and from the National Outcomes Program website [12], while demographic data were collected from the Italian National Institute of Statistics (ISTAT) website [13]. All data refers to the year 2019. From a clinical perspective, this study focuses on the hip replacement surgery procedure, an elective treatment where patients are generally prepared to travel long distances beyond their nearest provider [14]. To identify which variables mostly impact patient mobility, we applied the best subsets regression function of R (i.e., *regsubsets*) that tests all possible combinations of the predictor variables and then selects the best model according to the highest adjusted R squared value. The resultant regression model is reported in Equation 1 (note that adjusted R^2 = 0.66 and all variables are statistically significant, $p < 0.05$).

$$stay_{\%} = 42 - 0.05w + 0.6s + 0.07int_{intra} - 50ret_{intra} + 0.3bed_{intra} \quad (1)$$

where $stay_{\%}$ is the probability that the patient is cared in his/her region of residence, w is the number of waiting days to access the service (at regional level), s is the level of patient satisfaction due to the last hospital admission (at regional level), while int_{intra}, ret_{intra} and bed_{intra} describe, respectively, the number of interventions, the percentage of patients returned to hospital in the following 2 years from the intervention and the number of beds available in the orthopedics wards. Note that further indicators such as those related to the patient (i.e., income, education) have been discarded from the model as they were not statistically significant. Hospital-related indicators has been computed (for each municipality i) using Equation 2 based on a gravity model which relates the probability to access to a hospital with its capacity, quality and distance:

$$int_{intra}^{i} = \sum_{j\in\{Reg(i)=Reg(j)\}} INT_j R_j w_{i,j} = \sum_{j\in\{Reg(i)=Reg(j)\}} \frac{INT_j}{\sum_i pop_i * w_{i,j}} w_{i,j} \quad (2)$$

where R_j represents the weighted hospital-to-population index of hospital j, INT_j is the number of interventions carried out in hospital j and pop_i is the resident population of the municipality i. $w_{i,j}$ that represents the weighting distance between the hospital j

and the municipality *i* has been computed using the Sigmoid decay function. Based on Equation 2, an average value weighted by population of each indicator has been computed at province level. For further details please see [15].

2.2. Simulation process description

Figure 1 shows the main steps of the ABM simulation process. A set of 100.000 individuals are extracted from the whole target population using a stratified random sampling methodology considering two risk factors: age and gender. The second step (i.e., simulation) is composed by three activities: 1) a set of 1000 patients are extracted from the sample population to define the group of patients to be cared in a specific loop; 2) selected patients and hospitals, both represented by turtles, are placed over the patches of the environment based on their belonging municipality; 3) one patient at time is randomly picked up from the 1000 patients and the staying index (see Equation 1) is computed to assess the probability that the patient remains in his/her region to be cared. This index has been also applied to capture the level of attractiveness of each hospital located both within and outside the patient region of residence. Finally, the ABM simulation process stochastically determines the healthcare structure chosen by the patient. This process has been executed 52 times to simulate the access to care as a weekly procedure considering that the average length of stay for the primary total hip replacement is around 7 days [16].

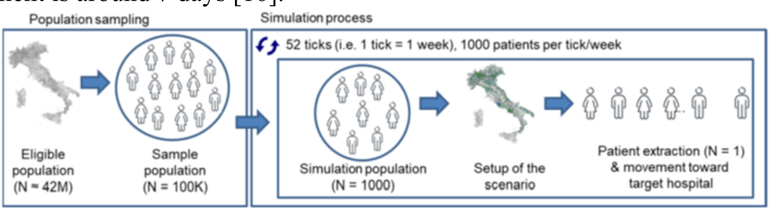

Figure 1. Agent-based modelling simulation process

To capture the accuracy (i.e., reproducibility) and the precision (i.e. repeatability) of the model five repeated sessions has been executed. From a statistical perspective, accuracy was assessed using the regression coefficient (R) between the simulated data and the original data, while precision was assessed using the Intraclass Correlation Coefficient (ICC(2,1)) to capture the intra-session reliability between observations.

3. Results

Figure 2 shows the Netlogo environment: on the left side the interface items adopted to control agents and the system are reported. In particular, the *n_ticks* and *n_patients* inputs allow to set, respectively, the number of weeks and the number of patients per week to be involved in the simulation. The output *patients_to_be_placed* facilitates the supervision of the process status capturing the number of patients located on the environment that has not been cared yet. On the right side of the window Netlogo integrates the map of the Italian territory divided by municipalities, colored depending on the passive mobility percentage, as reported in the specific legend.

The scatterplot diagram shown in Figure 3 highlights the linear regression between the passive mobility gathered from the ABM simulation (x-axis) and the passive mobility computed with the multiple linear regression model (y-axis). As clearly reported by R^2 (= 0.94) there is a very strong direct relationship between these two variables. A high correlation (R^2 = 0.66) is also reported considering the linear regression between the simulation mobility and passive mobility computed with the real hospital values. This result confirms the goodness of the simulation model. Considering the precision, the ICC(2,1) computed carrying out five sessions of ABM simulation resulted higher than 0.95 confirming the repeatability of the process.

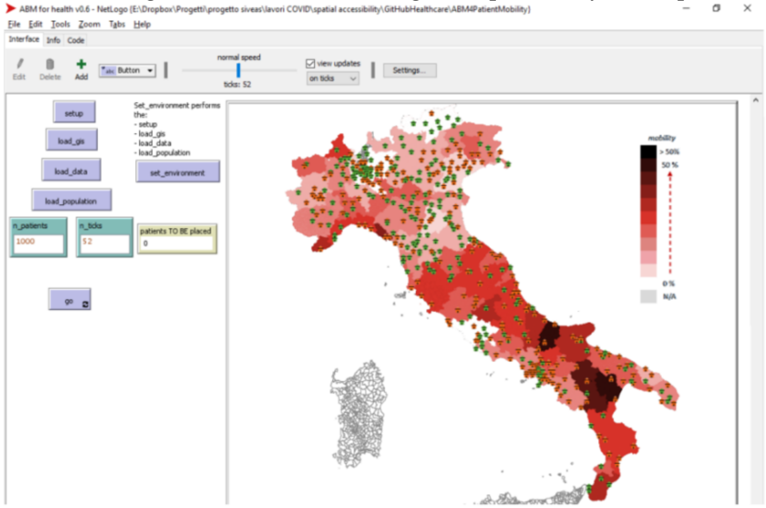

Figure 2. Netlogo environment highlighting the preliminary results of one simulation session

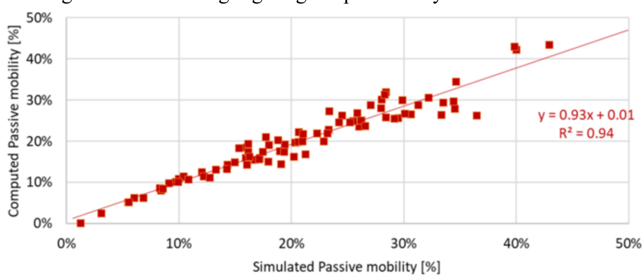

Figure 3. Correlation between the passive mobility gathered from the simulation model (x-axis) and the passive mobility computed with the multiple linear regression model (y-axix)

4. Discussion and Conclusions

The aim of this paper is twofold: on the one hand it would like to provide an ABM approach able to accurately simulate patient flow across the Italian regions and, on the other hand to determine which are the main individual, hospital and local factors influencing patient's mobility. To accomplish this task, we firstly defined a mathematical model able to accurately describe the dynamics of the patient-system interaction and define the probability that each patient involved in the simulation process accesses to an inter-regional structure. Based on this model, ABM stochastically determines the level of attraction of each structure and simulates the patient flows across the Italian regions. Preliminary results of the applicability of this approach highlight a high precision and accuracy in the description of patient mobility. This is clearly evident considering the very strong correlation coefficient between the simulated and the computed passive mobility. Moreover, the repeatability of the process is also confirmed by analyzing the low inter-session variability reported by the ICC. This high level of accuracy and precision confirms the goodness of the ABM simulation approach to describe this specific scenario. In this paper, we applied this methodology considering the hip replacement surgery procedure. However, this can also be applied to other elective surgery or curative services, to primary care services, or even to acute care services, such as intensive care.

The results reported in this paper focus on a real patient passive mobility scenario based on a prior knowledge of a population. Future works will detail the mathematical model to further analyze the main factors at individual, local and regional level responsible for attracting patients and contribute to active mobility. Moreover, simulation basic variables will be updated to verify how these changes may impact on patient mobility. This may help policy makers and hospital administrative professionals to capture to what extent these changes may help to contain these dynamics. For instance, this can be done by reducing the waiting times or improving the availability of services in a specific part of the territory that is not reached by the service under investigation. This can be done either by improving beds, personnel and resources on already established facilities or even providing an additional point of care.

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