ABM for simulating the access to elective surgery services: the issue of patient mobility in Italy

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Abstract. Patient mobility presents a significant challenge as it can have a detrimental impact on the financial sustainability of regional healthcare systems, given the large number of patients seeking care services outside of their region. To gain a deeper understanding of this phenomenon, it is essential to develop a behavioral model that accurately represents the interactions between patients and the healthcare system. To this end, we present an Agent-Based Modelling (ABM) to simulate the patient flow and identify the key factors that influence it. Our findings may provide policymakers with a novel perspective on the main drivers of patient mobility and potential strategies to address this issue.

Keywords: Patient mobility, Spatial Accessibility, Quality of care

1 Introduction

Patient mobility is considered as a proxy to appraise the quality and availability of hospital services [1,2] and to point out socio-economic disparities at local and regional level [3]. This is particularly evident in a decentralized tax-funded health system, like Italy, where patients can freely choose all over the territory [4]. While moving beyond regional borders is considered as an opportunity since patients may decide where to be treated on the basis of their needs, an unbalanced distribution and the heterogeneity of services may impact on patient choice. In particular, considering frail elderlies who reside in less populated areas where the competition between healthcare facilities is weak and patients generally choose their proximal service [5]. It has also been observed that patient choice is influenced by several individual factors, such as income, propensity to travel, education level, age, pathology complexity [4]. These aspects may represent an additional barrier that further emphasizes social inequalities for certain groups of population [6]. At the same time, a high and unbalanced distribution of complex procedures in high volume centers [7] may lead governments to put in place hospital consolidation and closure policies [8] that further influence the accessibility to specialized services. Even if the evidence suggests that centralization of services will improve quality of care also attracting high-skilled staff, long travel distances further unbalance equality of care as travelling may be prohibitive for patients with particular socio-economic and demographic conditions [9]. Moreover, interregional mobility has an economic implication [1] as compensation procedures are foreseen between the patient's region of residence and the one that provides the service. In Italy, mitigating mobility was one of the main actions planned within the Health Pact 2019–2021 [10] that highlights the necessity of mapping patient flows and drawing up a plan-to-stop passive mobility [1].

To further understand this phenomenon, it is necessary to define a behavioral model able to describe the patient-system interaction. In this study, to accomplish this task we rely on Agent-Based Models (ABMs) that describe how individual, population and health system characteristics can be expected to impact on interregional mobility. Previous studies have proposed the adoption of ABMs to provide greater understanding and explore policy options across a wide range of different social science settings [11]. However, despite their wide diffusion in the healthcare domain [12] and specifically on public health issues [13] to date only a limited number of studies have reported ABMs applications in patient decision making [14] and none of them are focused on accessing healthcare services. The adoption of ABMs may allow not only to synthesize prior knowledge and effectively simulate patient flow [15] but also help to understand how policy and procedural interventions could impact on its dynamics.

Starting from these premises the main aim of this study is to define an ABM to simulate patient flow across Italian regions, determining which are the main factors influencing it. This allows to significantly map the inequalities present at national and regional level as well as to provide an input for policy makers to capture to what extent capacity, quality and distribution of structures may contribute to the reduction of passive mobility. Moreover, this can be the starting point to identify and put in place actions that may contribute to identify and reduce social and territorial inequalities.

2 Materials and methods

2.1 Theoretical framework

Access to services is analyzed under two interrelated perspectives: i) patient mobility that describes the percentage of discharges of resident patients occurred in other regions; ii) the distance a patient is willing to travel for accessing high-quality and available services. Even though these phenomena represent two faces of the same coin, they are generally differently regulated. This is evident considering, for instance, that citizens living at the borders of their region may have close interregional hospitals so that travel distance is less in compare with those located in their region of residence. Also, determinants of these two phenomena are different: cross-border healthcare is mainly due to system characteristics, while willingness to travel is associated to patient's socio-economic and demographic features. For these reasons, in this paper, the patient flows have been analyzed considering these two aspects. In particular, to capture to what extent a patient is inclined to move outside his/her region of residence, we defined an econometric model able to assess the effect of selected independent variables on patient's passive mobility. To perform this task 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^2. The resultant regression model is reported in Equation 1 (note that adjusted $R^2 = 0.66$ and all variables are statistically significant, $p < 0.05$).

$$\overline{PM_i} = 42 - 0.05wait + 0.6sati + 0.07int_{intra} - 50ret_{intra} + 0.3bed_{intra} \quad (1)$$

Where *wait* is the number of days a patient has to wait to access the service (at regional level), *sati* 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 two years from the intervention and the number of beds available in the orthopedics wards. These indicators are computed (for each municipality *i*) using the methodology proposed in [2,16] and further described in the Annex provided in [17]. Other variables have been excluded from the model as they were not statistically significant. For the aim of our study $\overline{PM_i}$ has been adopted as a staying index ($stay_{\%}$) to determine the probability that a patient is cared in his/her region of residence.

Concerning the willingness to travel, we identify a set of individual socio-economic features that have a strong impact on the opportunity of patients to travel long distances to access to care services [1,3,18]. In our model we considered three conditions: 1) age lower than 65 years, 2) having a secondary education and 3) income higher than 18k Euros/year. These variables contributed to compute the maximum distance that a patient is willing to travel on the basis of the methodology proposed in [2,16] and further described in the Annex provided in [17].

Data have been gathered from: the Ministry of Health [19], the Italian Institute of Statistics (ISTAT) [20] and the Italian National Outcomes Programme (Programma Nazionale Esiti, PNE) [21]. All data refers to the year 2019. Note that islands were excluded from the analysis as residents cannot access to interregional facilities by car.

2.2 Agent Based Modeling process

The main steps of the ABM algorithm are summarized in Figure 1 and implemented using Netlogo 6.3. Code and databases are available online [17].

Firstly, a preliminary step was executed outside the Netlogo environment to define the reference population. In particular, a database (i.e., CSV file) containing the whole eligible population is structured considering, for each municipality, the main factors associated with the risk of needing hip replacement surgery: age, gender, prevalence of comorbidities and territorial distribution of interventions. This information is adopted to compute the probability that a patient with those characteristics is extracted and enrolled in the simulation study. An additional database storing a set of already extracted patients has been also set up to test the algorithm on a fixed population.

The first part of the process entails the initialization of the Netlogo environment and the loading of data (i.e., population, municipality and health system characteristics, distance table among municipalities). Using the Netlogo GIS extension each hospital is placed on its belonging municipality and initialized considering: 1) belonging region, province and municipality; 2) number of interventions the hospital can perform each week proportionally distributing int_j all over the year; 3) starting week when the hospital can enroll patients based on its waiting time. For instance, if waiting time is 126 days the hospital is available starting from the 19th week while in the previous 18 weeks is inaccessible.

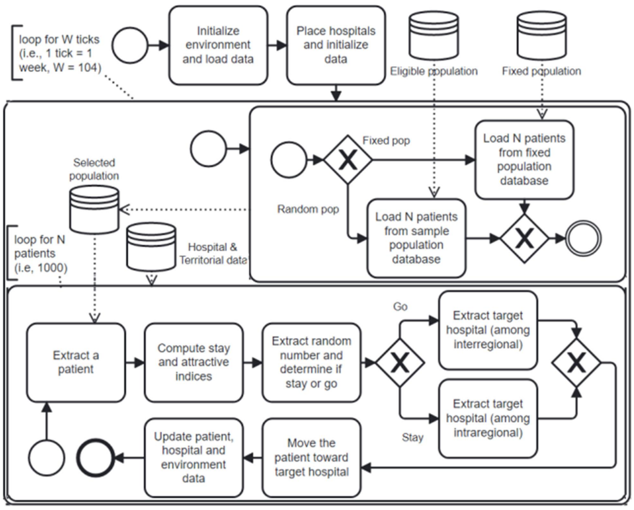


Fig. 1. Main steps of the simulation model

Once the environment is set up, the simulation process can start considering two calendar years each one divided in 52 weeks to simulate the access to care as a weekly procedure as the average length of stay for a hip replacement is around 7 days [22]. For each week, 1000 patients are enrolled, each one characterized by his/her socio-economic, demographic and territorial characteristics. Once a patient is extracted the target hospital where the patient is going to be treated is identified depending on the staying index (see Equation 1), the availability of hospital beds and the waiting time. To perform this task, the algorithm firstly captures whether the patient remains or not in his region of residence. This choice is performed generating a random number between 0 and 1, if it is lower than the staying index only intraregional hospitals will be considered, otherwise the algorithm will consider only interregional hospitals. The second step entails the choice of the relevant hospital. This is done by using a random weighted function where the probability of a structure to be chosen is proportional to its attractive index (see Annex provided in [17]). Finally, the patient moves toward the target and hospital capacity of the relevant week is reduced by 1. When the capacity of a hospital is negative, it can accept patients only in the subsequent week.

2.3 Statistical analysis

The Intraclass Correlation Coefficient (ICC) is adopted to capture the precision (i.e. repeatability) (ICC(2,1)) and the accuracy (i.e., reproducibility) (ICC(2,k)) of the

ABM approach. The analysis of territorial inequalities has been performed using the Getis-Ord GI* statistic that classifies municipalities within hot, cold and not significant spots on the basis of the level of patient's passive mobility.

3 Results

3.1 Robustness of the simulation model

Table 1 highlights the level of accuracy and precision of the model comparing results of the simulation with real data extracted from the PNE and regression data computed using Equation 5. The algorithm has been tested considering two simulation sessions each one composed by 50 repetitions: in the first session (*Random*) patients have been randomly extracted from the eligible population database based on relevant risk factors, so that patients distribution and characteristics varied between repetitions. In the second session (*Fixed*), patients are extracted from the fixed population database in the same order so that their distribution and characteristics matched across repetitions.

Table 1. Level of accuracy and precision of the simulation model

Mobility	Session	Original data	Accuracy ICC(2,k)	Precision ICC(2,1)
Passive	Random	Regression	0.99 (0.88-0.99)	0.95 (0.94-0.96)
		Real	0.88 (0.81-0.92)	
	Fixed	Regression	0.98 (0.97-0.99)	0.95 (0.93-0.96)
		Real	0.86 (0.79-0.91)	
Active	Random	Regression	0.97 (0.92-0.99)	0.90 (0.84-0.95)
		Real	0.93 (0.82-0.98)	
	Fixed	Regression	0.97 (0.91-0.99)	0.95 (0.91-0.98)
		Real	0.93 (0.81-0.97)	
Flow	Random			0.98 (0.98-0.99)
	Fixed			0.98 (0.98-0.99)

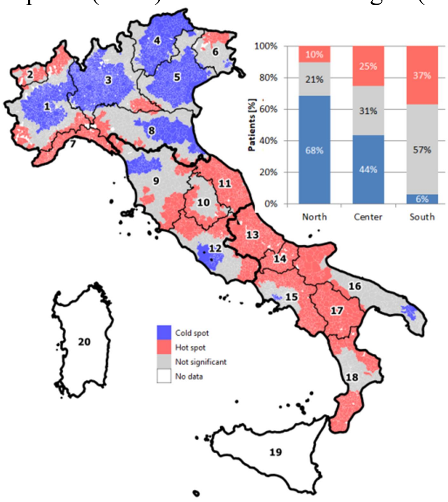
ICC values confirm the high reproducibility of the model using both fixed and random populations, with particular attention on the comparison with the regression data of passive mobility (ICC > 0.98). Also results on active mobility can be considered satisfactory (ICC > 0.97) for both fixed and random populations. Looking at the comparison with real data, ICCs are higher than 0.86 for passive mobility and 0.93 for active mobility, confirming the high reproducibility of the model, noting that the coefficient of determination (R^2) between real and regression data is 0.67.

Also the precision follows a similar pattern where the passive mobility results high repeatable (ICC = 0.95) for both fixed and random populations, while a low level of repeatability is found for active mobility and random population (ICC = 0.90). Interesting to note that active mobility rates are higher repeatable when using fixed populations with a ICC equal to 0.95. Finally, the high repeatability of the model is confirmed considering the patient flow between regions (i.e., patients that move from a region A of residence to a specific region B) for both populations (ICC > 0.98).

These results underline that no significant differences are found when using fixed or random populations, with the only exception of active mobility. Thus, the adoption of different populations seems to not have an impact on patient flow.

3.2 Patient mobility as a health inequality indicator

The map in Figure 2 shows the result of the hotspot analysis performed considering passive mobility computed at municipality level, based on random population. This map is complemented by a histogram that summarizes the percentage of patients classified in each spot zone within three statistical regions (i.e., north, center and south). Moreover, Figure 3 highlights this distribution at regional level. The map highlights the presence of big clusters of municipalities characterized by concentrations of high or low value of passive mobility, located in well-defined zones of the country. The hot spot zones (i.e., high mobility) mostly interest the south of Italy, with some differences between regions. For instance, a consistent part of the territory is included within the neutral area in the north of Campania (id 15), south of Puglia (id 16) and center of Calabria (id 18). This distribution underlines the level of inequalities of hospital accessibility at regional level. On the other side, southern regions such as Abruzzo (id 13), Molise (id 14) and Basilicata (id 17) have almost the whole territory, and hence population, classified within the hot spot area, underling a certain level of equality at local level even if with a high level of mobility. Cold spots, that indicate low mobility and hence good condition of accessibility and quality of care, are almost irrilevant in these regions, with exceptions found around the city of Naples in Campania (id 15) and of Lecce in Puglia (id 16).

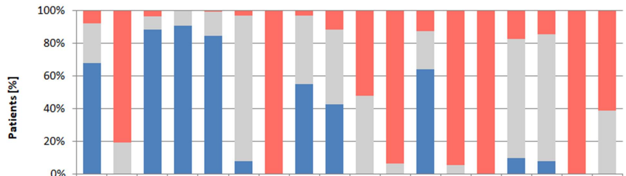


Code	Region	
1	Piemonte	North
2	Valle d'Aosta	North
3	Lombardia	North
4	Trentino-Alto Adige	North
5	Veneto	North
6	Friuli-Venezia Giulia	North
7	Liguria	North
8	Emilia-Romagna	North
9	Toscana	Center
10	Umbria	Center
11	Marche	Center
12	Lazio	Center
13	Abruzzo	South
14	Molise	South
15	Campania	South
16	Puglia	South
17	Basilicata	South
18	Calabria	South
19	Sicilia	
20	Sardegna	

Fig.1. Hotspot analysis. At the bottom-right of the figure the histogram summarizes the percentage of patients classified within the spot areas for each statistical region.

Looking at the north of the country, a low patient mobility (cold spot) is present in the majority of the regions, such as Lombardia (id 3), Trentino Alto Adige (id 4) and

Veneto (id 5), where a limited number of patients are classified within the hot spot area. Among them Piemonte (id 1) has the highest inequality level: despite the majority of patients fall within the cold spot area, part of the region is classified within the hot spot and neutral areas. Conversely, Valle d'Aosta (id 2) and Liguria (id 7) report a peculiar situation with a high percentage of patients within the hot spot cluster and consequently with a low passive mobility equally distributed over the territory. Note that in these regions an important barrier that can influence patient choice is the conformation of the territory considering their proximity to the mountains that highly increase travel distances due to mobility infrastructures.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
	North								Center				South					
Hot spot	8%	81%	4%	0%	0%	3%	100	3%	12%	52%	94%	13%	95%	100	17%	14%	100	61%
Not significant	25%	19%	8%	9%	15%	90%	0%	42%	46%	48%	6%	23%	5%	0%	73%	78%	0%	39%
Cold spot	68%	0%	88%	91%	85%	7%	0%	55%	43%	0%	0%	64%	0%	0%	10%	8%	0%	0%

Fig.2. Distribution of within the hot, cold and non-significant areas at regional level

Similarly to the south, also the center of Italy reports criticisms in different regions. For instance, in Lazio (id 12) on the one hand the presence of Rome (the city with the highest hospital capacities in the country) attracts resident patients, but on the other hand, as seen for Piemonte, patients living at the borders of the region and distant from Rome are willing to access to interregional instead of intraregional facilities.

4 Discussion and conclusions

The paper presents an ABM approach for modelling patient mobility in accessing to hospitals across Italian regions to capture inequalities of hospital services at both national and regional levels. The study has been based on the hip replacement procedure as it represents a case study where around 20% of patients are treated outside their region of residence [21]. From a policy perspective, understanding what are the main factors underlying this migration flow represents an important concern for both healthcare professionals and policy makers that need to put in place strategies to mitigate this phenomenon. To model patient flow across regions, we firstly defined a mathematical model that accurately describes the dynamics of the patient-system interaction and defines the probability that each patient involved in the simulation process accesses to an interregional structure. This has been done applying an econometric (linear) model that identifies which are the main individual, hospital and territorial factors influencing passive mobility. Based on this model, ABM determines the probability that a patient remains in his/her region of residence or move to another region to access to hip replacement service. This is done by computing for each hospital an attraction index based on its quality and capacity as well as on the distance from the patient. Patient queue and hospital availabilities are also included in the simulation process so to consider hospital saturation and waiting times.

The results section presents a preliminary analysis of the applicability and robustness of this approach highlighting the suitability of the proposed ABM solution to describe this specific scenario with a very strong correlation between the simulated and the computed passive and active mobility. Patient flows resulted from the application of ABM have been subsequently analyzed to capture the level of inequalities present over the Italian territory. In fact, portions of the country or of specific regions with high mobility rate are associated with low quality and/or accessibility of services due to various reasons such as high waiting times, low patient satisfaction, limited number of beds, low number of interventions, high distance from the hospital. To statistically determine the distribution of high-quality and low-quality areas across the country, we applied a hotspot analysis that clustered municipalities and determined in which portion of each region patients are willing to travel outside their residence. At national level, the hotspot analysis highlighted the low level of accessibility and quality of services offered in the south of Italy in compare with the north of Italy where different zones not only have a low level of passive mobility but are also characterized by a high level of patient attraction from both nearby and remote regions. Beyond this level of inequality present in the country with the peninsula divided in two (north vs. central-south), specific concerns can be appraised at regional level. They are generally present where hospitals are concentrated in or around one big city. This is the case of Lazio and Piemonte where a consistent number of patients have a high access to intraregional services, but despite the high capacity of hospitals, several municipalities fall within the low-level of accessibility area.

In conclusion, this study demonstrates the feasibility of ABM to simulate patient flow across Italian regions for accessing hospital services. Moreover, we applied the results of the simulation model to determine the level of inequality in the quality and distribution of structures both at regional and national level. This preliminary analysis may need further investigations to determine to what extent each factor influences patient mobility. It can support policy makers in mapping patient flows, investigating reasons for patient mobility and put in place actions that are able to mitigate this phenomenon. From a methodological perspective this algorithm should be further analyzed and improved under two interrelated aspects: 1) the behavioral model should be extended including other territorial, system and individual variables; 2) regional borders should be removed in the ABM process in order to consider each hospital as an attractor for the patient. Both aspects require the availability and access to high level detailed data not limited to passive mobility at province level but that at least include patient flow across regions. Moreover, simulation variables may be updated to verify how these changes impact on patient mobility. This may help policy makers to predict how structural changes may contain patient mobility, for instance, by reducing waiting times or improving the availability of services in specific isolated territories.

Finally, although in this paper we applied this methodology on a specific scenario, its application should be extended to other elective surgery or curative services, primary care services, acute care services or critical services, such as intensive care.

References

1. Nante, N., Guarducci, G., Lorenzini, C., Messina, G., Carle, F., Carbone, S., Urbani, A.: Inter-Regional Hospital Patients' Mobility in Italy. Healthcare 9(9), 1182 (2021).
2. Pecoraro, F., Luzi, D., Clemente, F.: The impact of Hospital accessibility on interregional patient mobility in Italy. Stud Health Technol Inform 294, 684–688 (2022).
3. Rubino, C., Di Maria, C., Abbruzzo, A., Ferrante, M.: Socio-economic inequality, interregional mobility and mortality among cancer patients: A mediation analysis approach. Socio-Economic Planning Sciences 82, 101247, 2022.
4. Aggarwal, A., Lewis, D., Mason, M., Sullivan, R., Van Der Meulen, J.: Patient mobility for elective secondary health care services in response to patient choice policies: a systematic review. Medical Care Research and Review 74(4), 379-403, 2017.
5. Victoor, A., Delnoij, D.M.J., Friele, R.D., Rademakers, J.J.D.J.M.: Determinants of patient choice of healthcare providers: A scoping review. BMC Health Serv Res 12, 272, 2012.
6. Ricci, A., Barzan, E., Longo, F.: How to identify the drivers of patient inter-regional mobility in beveridgean systems? Critical review and assessment matrix for policy design & managerial interventions. Health Services Management Research 34(4), 258-268, 2021.
7. Avdic, D., Lundborg, P., Vikström, J.: Estimating returns to hospital volume: Evidence from advanced cancer surgery. Journal of Health Economics 63, 81–99, 2019.
8. Carroll, C.: Impeding access or promoting efficiency? Effects of rural hospital closure on the cost and quality of care. NBER Working Paper Series 2019.
9. Rechel, B., Wright, S., Edwards, N., Dowdeswell, B., McKee M.: Investing in hospitals of the future, World Health Organization, Copenhagen (2009).
10. Italian State-Regions Standing Conference. Health Pact 2014-2016. www.salute.gov.it/imgs/C_17_pagineAree_2986_listaFile_itemName_8_file.pdf.
11. Conte, R., Paolucci, M.: On agent-based modeling and computational social science. Frontiers in psychology 5, 668, 2014.
12. Sulis, E., Mariani, S., Montagna, S.: A survey on agents applications in healthcare: Opportunities, challenges and trends. Comput Methods Programs Biomed 107525, 2023.
13. Tracy, M., Cerdá, M., Keyes, KM.: Agent-Based Modeling in Public Health: Current Applications and Future Directions. Annu Rev Public Health 39, 77–94, 2018.
14. Han, Y., Yoon, S. W., Khasawneh, M. T., Srihari, K.: Agent-Based Modeling of Patients' Hospital Choice and Bypass Behavior in Rural Areas. In IIE Annual Conference. Proceedings. Institute of Industrial and Systems Engineers (IISE) (2012)
15. Boyd, J., Wilson, R., Elsenbroich, C., Heppenstall, A., Meier, P.: Agent-Based Modelling of Health Inequalities following the Complexity Turn in Public Health: A Systematic Review., Int J Environ Res. Public Health 19, 16807, 2022.
16. Pecoraro, F., Luzi, D., Clemente, F.: Spatial Inequity in Access to Intensive Care Unit Beds at Regional Level in Italy. Stud Health Technol Inform 281,809-813, 2021.
17. The code for the model and the relevant databases are available online at https://github.com/fabripec/ABM4PatientMobility
18. Balia, S., Brau, R., Marrocu, E.: Interregional patient mobility in a decentralized healthcare system. Regional Studies 52(3), 388-402, 2018.
19. Ministry of Health. National healthcare service database. 2019, www.salute.gov.it/portale/documentazione/p6_2_8_1_1.jsp?lingua=italiano&id=6.
20. Italian National Institute of Statistics (ISTAT), http://dati.istat.it/?lang=en.
21. Italian National Outcomes Programme (PNE), https://pne.agenas.it/.
22. Foote, J., Panchoo, K., Blair, P., Bannister, G.: Length of stay following primary total hip replacement. Ann R Coll Surg Engl 91(6), 500-504, 2009.