The Economic Burden of Hip Fractures among Elderly Patients in Ireland: A Combined Perspective of System Dynamics and Machine Learning

Mahmoud Elbattah
National University of Ireland Galway
m.elbattah1@nuigalway.ie

Owen Molloy
National University of Ireland Galway
owen.molloy@nuigalway.ie

Abstract

Population ageing is increasing in a rapid pace worldwide, and especially within developed countries. Extraordinary economic challenges are therefore in prospect with regard to healthcare delivery. In this respect, healthcare executives increasingly need tools that can accurately assess the impacts of the foreseen demographic transition. The paper investigates the economic implications in relation to the incidence of hip fractures among elderly patients in Ireland. A combined approach is adopted that utilises System Dynamics (SD) and machine learning. At the macro-scale level, an SD model is used to produce projections of elderly populations who are susceptible to sustain hip fractures. In addition, the SD model is disaggregated to properly depict the demographic structure of the healthcare system in Ireland. At the micro-scale level, machine learning models are used to make careful predictions on the inpatient length of stay and discharge destinations for simulation-generated patients. The study is claimed to deliver useful insights regarding the potential economic burden on the Irish healthcare system implied by elderly hip-fracture patients. More broadly, we attempt to provide a multi-methodology perspective that combines simulation modeling and machine learning towards increasing the confidence and credibility of the simulation model predictions for decision making purposes.

Keywords:
System Dynamics; Machine Learning; Elderly Healthcare; Hip Fracture Care.

1. Introduction

In tandem with climate change and global terrorism, the UN identified population ageing as one of the three main global challenges [1]. In Europe, the proportion of people aged 65 years or over has already exceeded that younger than 15 years in 2008, and that proportion is expected to double by 2060 [2]. More importantly, the proportion of very old people aged 80 years or over is expected to triple between 2008 and 2060 [3]. Likewise in Ireland, the population has been experiencing a pronounced transition of ageing. The Health Service Executive (HSE) of Ireland reported in 2014 that the increase in the number of people over 65 is approaching 20,000 per year [4]. Population ageing is therefore expected to have profound impacts on a broad range of economic and social areas. Figure 1 plots the trend of ageing worldwide as reported by the UN [5].

In the context of elderly-related care, the study focused its attention on the care scheme of hip fracture in Ireland. Hip fractures are a major cause of injuries and morbidity among elderly patients. As acknowledged by numerous studies [6-8], hip fractures were observed to be exponentially increasing with age, despite the existence of rate variability from country to another. Furthermore, the burden of hip fractures on the healthcare system may unavoidably increase owing to the continuous improvement of life expectancy of the population [9-10].

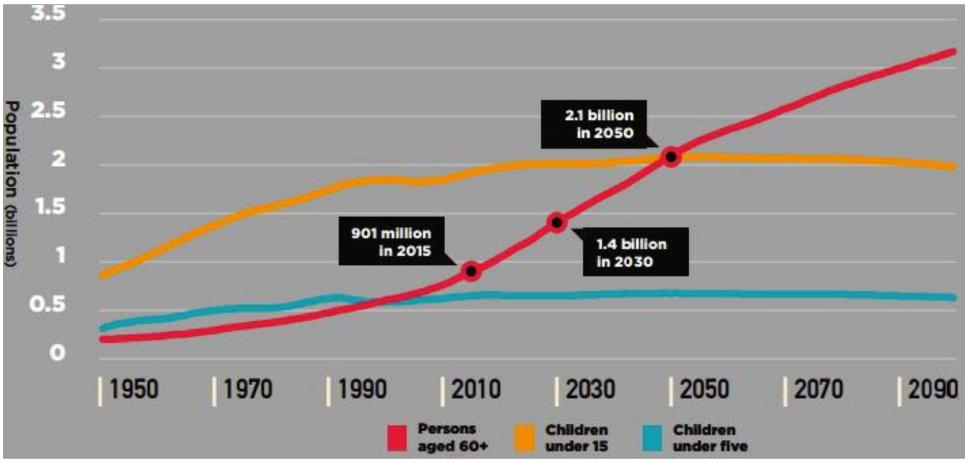


Figure 1. Global projections of the elderly aged 60 and over compared to children under 15 (1950- 2090) [5].

In light of that, the paper mainly aimed at estimating the potential economic cost in relation to hip fracture treatment for elderly patients in Ireland. The economic burden is two-fold: i) Direct costs, and ii) Indirect costs. The direct costs typically include the amount of expenditure spent on ED (Emergency Department) admission, and inpatient/outpatient care. While indirect costs can involve various adverse effects on the quality of life. However, the study endorsed only the direct costs, which can be mostly tangible to quantify and assess. The direct costs of treatment are highly contingent on the inpatient length of stay and the discharge destination whether home, or a long-stay care such as nursing home for example. As a result, it was imperative to endorse other auxiliary questions related to the inpatient length of stay and discharge destination in order to be able to make a valid estimation of that economic burden. Table 1 lists the principal and auxiliary questions in detail.

Table 1. Questions of interest.

Questions	
Principal Question	**Auxiliary Questions**
Q1) With the growing trend of population ageing, what is the potential economic burden of elderly hip-fracture patients on the healthcare system in Ireland over the next 10 years?	Q1) What is the expected proportion of elderly patients discharged to home, or long-stay care after the hip fracture treatment?
	Q2) Given the characteristics of an elderly hip-fracture patient, how to predict the length of stay in acute facilities?
	Q3) Given the characteristics of an elderly hip-fracture patient, how to predict the discharge destination?

Specifically, we attempted to make contributions in two aspects. First, useful insights were delivered in relation to the expected economic burden of hip fracture care owing to population ageing. The insights were provided based on a well-rounded picture corresponding to the demographic profiles and structure of the healthcare system in Ireland. Second, the study presented the prospective application of a multi-methodology approach that combined simulation modeling and data-driven techniques using machine learning. Machine learning is used in an attempt to improve the predictive power of the simulation model, in turn improving its credibility for decision making.

2. Scale of the Problem of Hip Fractures in Ireland

Around 3,000 people sustain hip fractures annually in Ireland [15]. Specifically, the rates of fracture for the total population aged 50 years and over were reported as 407 and 140 per 100,000 for females and males respectively [16]. It was also reported that about 80% of the elderly patients are over 75 years of age [17]. Therefore, these figures can inevitably increase owing to the growing trend of ageing as shown in Figure 2 that plots projections of elderly population in Ireland from 2016 to 2026.

From an economic perspective, hip fractures can represent a major burden on the Irish healthcare system. According to the HSE, hip fractures were identified as one of the most serious injuries resulting in lengthy hospital admissions and high costs [18]. The median LOS was recorded as 13 days, and less than one-third go directly home after their hospital treatment [15]. As a result, numerous studies attempted to investigate the costs associated with hip fracture incidents [19-24]. For instance, the cost of treating a typical hip fracture was estimated around €12,600 [18], while a different study reported a higher cost of €14,300. Given these statistics, it can be inferred that hip fractures are, and will be, a major concern to healthcare in Ireland, and there will be a critical need to develop evidence-based strategies in order to meet the foreseen challenges.

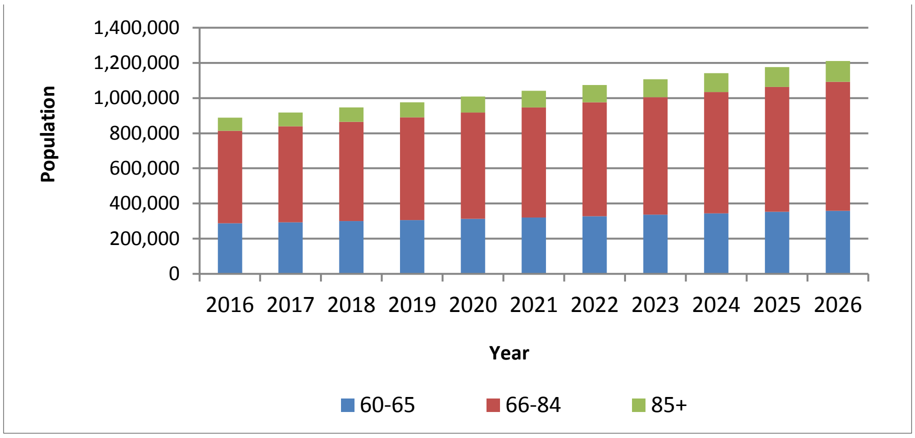


Figure 2. The projections of elderly population in Ireland (2016- 2026) [25].

3. The Status of the Healthcare System in Ireland

A sound simulation-based study should start with understanding the problem or system of interest [26]. In this sense, understanding the underlying structure of the Irish healthcare system represented a major concern of the study. This section delivers a concise picture of the underpinning components of the healthcare system in Ireland.

The healthcare system in Ireland has been undergoing a radical reform based on a phased strategy since 2012. The fundamental goal of the reform is to transition the healthcare system towards the integrated delivery of healthcare services. The integrated care is adopted as a means to improve the services in relation to accessibility, quality and user satisfaction of care services. According to the WHO, integrated care is a concept that brings together inputs, delivery, management and organisation of services related to diagnosis, treatment, care, rehabilitation and health promotion [27].

The transitional arrangements included structuring the Irish healthcare system into 9 geographic regions, called “Community Health Organizations”, commonly abbreviated as CHO. The newly established CHOs are aimed to serve as integrated service areas that can deliver better, more integrated and responsive services to people in the most appropriate setting. Every CHO is responsible for the delivery of primary and community-based services within national frameworks responsive to the needs of local communities. Specifically, the CHOs include 90 Primary Care Networks (PCNs) across the country, where each PCN is intended to serve an average population of 50,000 inhabitants. The quality of care provided within a PCN will highly depend on how healthcare staff are organised in a way that promotes teamwork to responsively address needs of local people. Figure 3 shows the geographic boundaries of the 9 designated CHOs.

Equally important, the reform strategy endeavours to reorganise public hospitals into a small number of hospital groups, each with its own governance and management. The hospital groups are named as follows [28]: i) Dublin North East, ii) Dublin Midlands, iii) Dublin East, iv) South/South West, v) West/North West, and vi) Midwest. On one hand, the formation of hospital groups can harness the benefits of increased independence and a greater control at local level. On the other hand, grouping hospitals can allow appropriate integration in order to improve patient flow across the continuum of care.

Figure 3. The geographic boundaries of the Community Health Organisations (CHOs) [43].

4. Approach Overview

The study endeavored to embrace a multi-methodology approach. The needs and benefits of multi-methodologies were acknowledged within different contexts. For instance, two arguments were made by study [12]. First, the complexity and multi-dimensionality of real-world problems require using different methodologies to enable focusing on different aspects of the situation. Second, a problem can go through different phases, and more than one methodology might be required to tackle all phases. In addition, study [13] argued that the triangulation of a situation using different methodologies can generate new insights while enhancing confidence in the results through a reciprocal validation.

In our case, the adopted approach attempted to combine simulation modeling and machine learning. On one hand, System Dynamics is a well-established simulation methodology that can be used to explore the behaviour of systems over time. Further, an SD model can help understand the long-term implications in situations where the complexity of change is compounded by secondary effects [11]. On the other hand, machine learning has become an instrumental artifact for building powerful prediction models. Specifically, we utilised machine learning to provide robust data-driven predictions of variables that have a significant influence on the problem of interest. The incorporation of the two methods is claimed to yield more credible results with respect to decision making scenarios.

In a pipelined fashion, the approach comprised four stages. The first stage included the development of an SD simulation model, which provided the population projections of elderly patients. The SD model was disaggregated in accordance with the structure of the Irish healthcare system as described in Section 5.4. Secondly, the produced projections were used to generate individual elderly patients, whereas each patient was assigned a set of characteristics that accurately mimicked reality. The simulation-generated patients represented a fine-grained perspective that can be used to estimate patient outcomes on individual basis. Thirdly, two machine learning models were developed in order to predict the LOS and discharge destination for every elderly patient generated by the simulation model. The prediction models were developed and tested using Microsoft Azure Machine Learning [14]. Based on the predicted outcomes, the cost of treatment is calculated for every patient. Finally, the aggregation of costs can provide an overall view of the economic burden of hip fractures. Figure 4 sketches an overview of the approach.

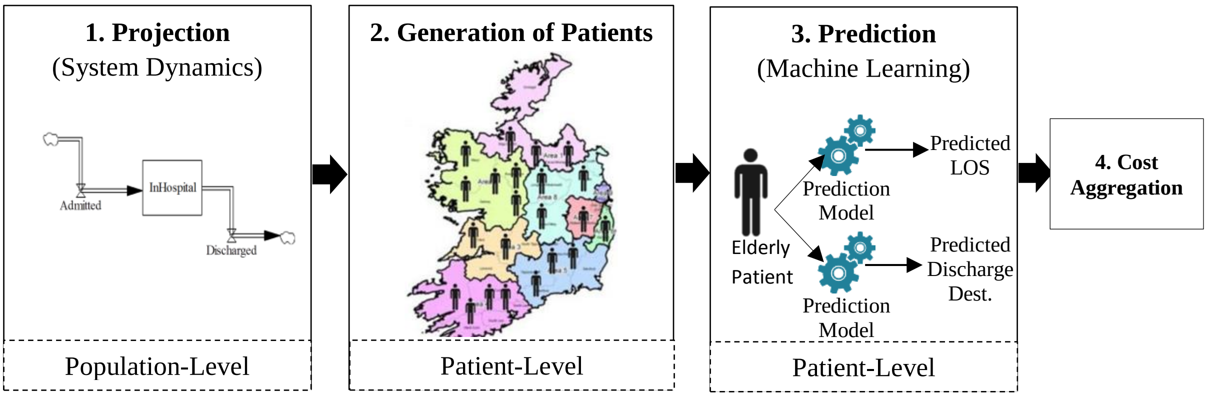


Figure 4. Overview of the approach stages.

5. System Dynamics Model:

5.1 Sources of Data

The study utilised a dataset acquired from the Irish Hip Fracture Database (IHFD) [29]. The IHFD repository is the national clinical audit developed to capture care standards and outcomes for hip-fracture patients in Ireland. The IHFD records contain ample information about the patient's journey from admission to discharge. Specifically, a typical patient record included 38 data fields such as gender, age, type of fracture, date of admission, time to surgery and LOS. The dataset consisted of 2,024 patient records for the year 2013. Full descriptions of the dataset fields were also available in the form of a data dictionary [30]. Mainly, the assumptions, limitations and parameters of the simulation model were constructed based on admission and discharge records from that dataset.

With respect to population statistics, the study used projections prepared by the Central Statistics Office (CSO) [25]. The population information contained comprehensive information about the population in terms of age groups and sex. However, the simulation model focused only on population aged 60 years and over, in line with the study scope. Furthermore, we acquired additional demographic statistics from the HSE Health Intelligence. The demographic information was prepared in connection with the 9 CHOs that structure the healthcare system in Ireland as described in Section 3. Although, the CHOs' statistics included only the year 2014, they were useful for setting necessary assumptions, which are described in the next section. Figure 5 plots the reported elderly populations in 2014 with respect to every CHO.

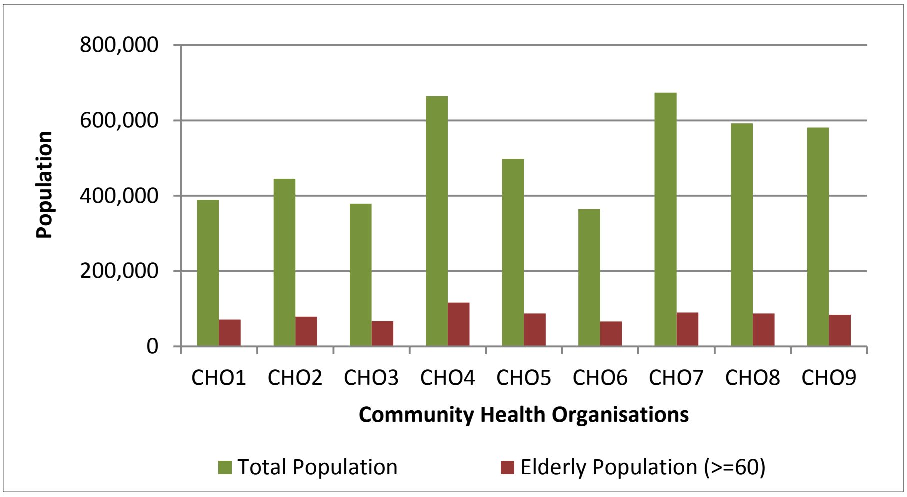


Figure 5. The population profiles of the 9 CHOs in 2014. The left-sided column represents the total population, while the right-sided column represents the elderly population aged 60 and over.

5.2 Model Assumptions and Simplifications

A set of assumptions and simplifications were decided while maintaining the simulation model as a reasonably approximate representation of the actual system. Table 2 presents what assumptions were made and why.

Table 2. Model assumptions and simplifications.

Assumption / Simplification	**Purpose / Reason**
The rate of hip fracture in the total population aged 60 and over was set as 407 for females and 140 for males per 100,000.	The rate was defined by [16].
Elderly patients were assumed as those aged 60 and over, although usually considered as aged 65 and older [31].	To conform to the preset hip fracture rate, which included those aged 60 and over.
The model did not consider the scenario of patient transfer from an acute hospital to another during treatment course.	Only for simplification, where the treatment course was bounded within a single acute hospital.
The elderly population for each CHO was computed by applying a (fixed) percentage of the nation-wide projected population on a yearly basis from 2016 to 2026. For example, the elderly population of CHO1 was computed as 9.5% of the total elderly projected population in 2016, whereas 9.5% was the actual percentage in 2014.	Due to lack of population information about the 9 CHOs. The study obtained the population profiles of the CHOs for the year 2014 only.

5.3 Initial Model

The initial model provided a bird's-eye view of the care scheme of hip fracture with respect to the principal question of interest. The preliminary version of the model aimed at capturing the relationships within the system components in an SD manner. Specifically, the model focused on capturing the major dynamic behaviour in relation to the continuous growth of ageing, and the consequent implications on the incidence of hip fractures among elderly patients. The model defined the main actors within the system as follows: i) Elderly patients, ii) Acute hospital, and iii) Discharge destinations including home or long-stay care facilities. However, the initial model did not accurately describe the structure of the healthcare system in Ireland as described in Section 3. Figure 6 illustrates the initial SD model. Table 3 lists the model variables and Table 4 presents the model equations.

The model included a single reinforcing loop implied by the elderly patients of a fragility history, who are susceptible to re-sustain hip fractures or fall-related injuries. According to the HSE [18], one in three older people fall every year and two-thirds of them fall again within six months.

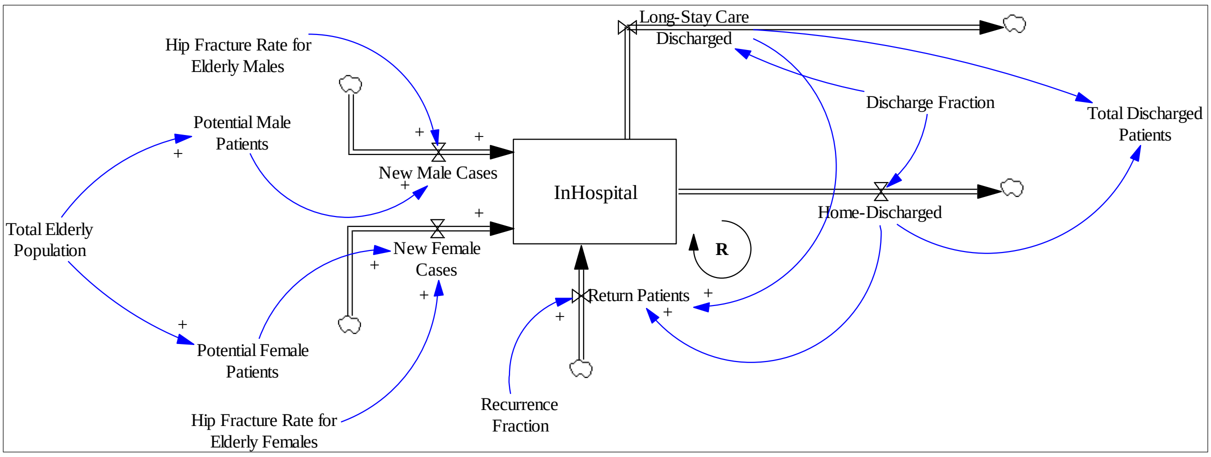


Figure 6. Initial SD Model. The model depicts two potential discharge destinations as Home or Long-Stay Care. The discharge destinations will be excluded from the disaggregated model, and will be predicted by machine learning models on individual patient basis.

Table 3. Model variables.

Variable	**Description**
Total Elderly Population	Represents the total number of elderly population, aged 60 and over, nationwide in a particular year.
Potential Male Patients	Total male patients aged 60 and over.
Potential Female Patients	Total female patients aged 60 and over.
Hip Fracture Rate for Elderly Males	The rate of hip fracture in the total elderly male population = 140 cases per 100,000.
Hip Fracture Rate for Elderly Females	The rate of hip fracture in the total population aged 60 and over =407 for females per 100,000.
InHospital	Stock variable represents the total number of elderly hip-fracture patients in acute hospitals nationwide.
Discharge Fraction	Proportion of total elderly patients discharged to home or long-stay care.
Total Discharged Patients	Represents the total number of elderly patients discharged to home and long-stay care.
Recurrence Rate	The rate that defines the proportion of discharged patients who are susceptible to re-sustain a hip fracture and return to an acute hospital.

Table 4. Model equations.

Equation	**Type**
(1) Hip Fracture Rate for Elderly Males = 140 cases per 100,000.	Auxiliary
(2) Hip Fracture Rate for Elderly Females = 407 cases per 100,000.	Auxiliary
(3) New Male cases = Hip Fracture Rate for Elderly Males * Potential Male Patients	Inflow
(4) New Female Cases = Hip Fracture Rate for Elderly Females * Potential Female Patients	Inflow
(5) Home-Discharged= InHospital * Discharge Fraction	Outflow
(6) Long-Stay Care Discharged= InHospital * (1-Discharge Fraction)	Outflow
(7) Recurrent Patients = (Home-Discharged * Recurrence Rate) + (Long-Stay Care Discharged * Recurrence Rate)	Inflow
(8) InHospital =Integ((New Male cases+ New Female Cases) - (Home-Discharged + Long-Stay Care Discharged) + Recurrent Patients, Initial Value)	Stock

5.4 Disaggregated Model

The preliminary model did not properly consider the structure underlying the Irish healthcare system. In contrast, the disaggregated model aimed to provide an accurate representation of the healthcare system in terms of the 9 CHOs, and their associated elderly populations. It was important to disaggregate the preliminary model, so that the results can be interpretable with reference to the geographic areas that structure the healthcare system. Furthermore, the discharge destinations (Home, Long-Stay Care) were excluded from the disaggregated model. The discharge destinations were predicted on individual patient basis by machine learning models. Figure 7 illustrates the disaggregated model. The model was implemented using the R package deSolve [32].

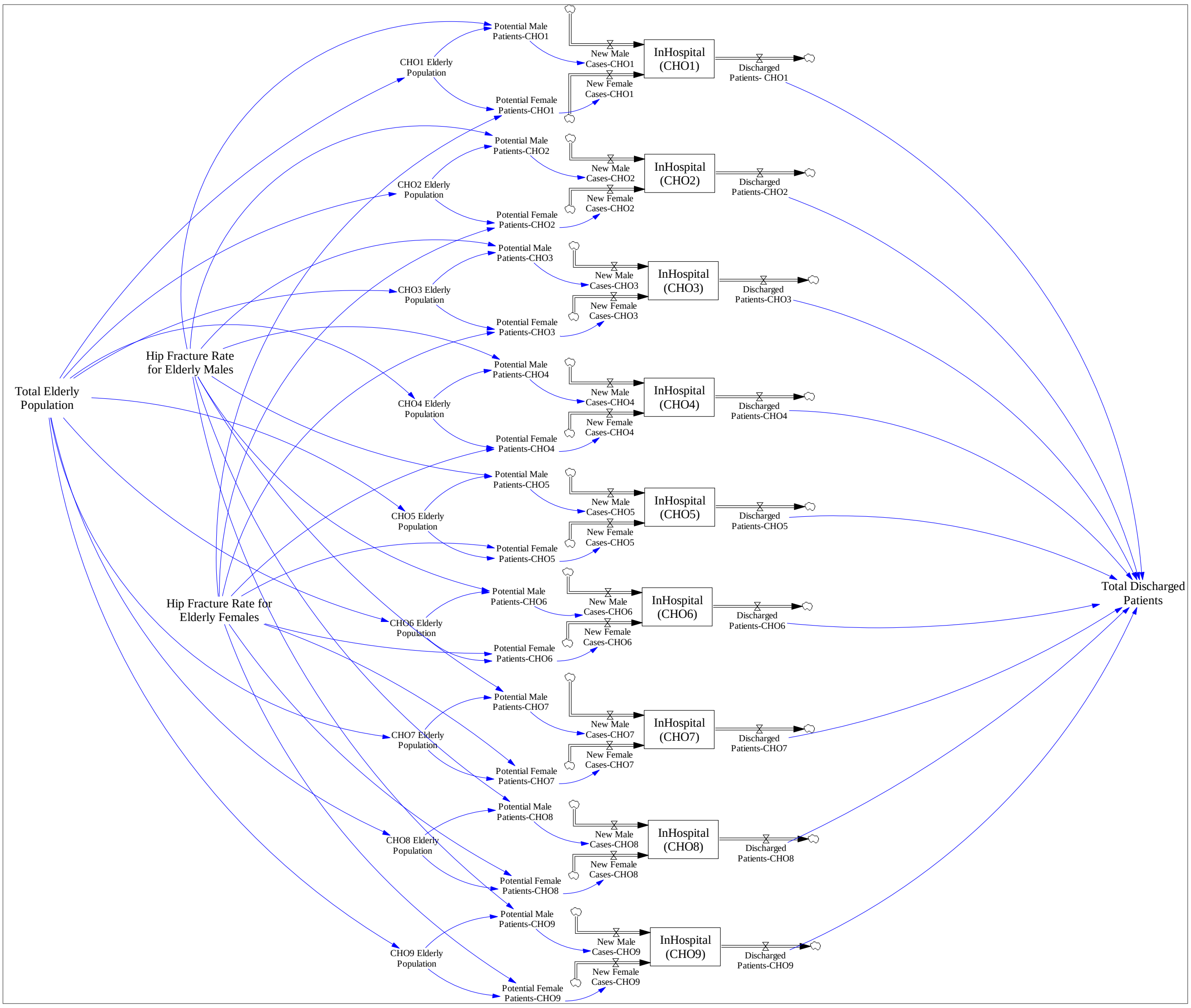


Figure 7. Disaggregated SD Model.

6. Generation of Patients

Based on the projections produced the disaggregated SD model, individual patients were generated within every CHO. Every patient was assigned a set of characteristics including: i) Age, ii) Sex, iii) Fracture Type, iv) Fragility History, v) ICD-10 Diagnosis, vi) Residence Area, and vii) Host Hospital. The values of the characteristics were sampled based on the distributions within the real dataset extracted from the IHFD (Section 5.1). The generation process was implemented using the R language. The total number of generated patients reached 1,599,000 for 50 simulation experiments. Table 5 presents the counts of elderly patients generated within every CHO.

Table 5. Counts of patients generated per CHO over 50 simulation experiments.

Community Health Organisation (CHO)	No. of Simulation-Generated Patients
CHO1	151,850
CHO2	169,550
CHO3	142,450
CHO4	247,750
CHO5	187,050
CHO6	140,750
CHO7	191,900
CHO8	187,050
CHO9	180,650

7.0 Prediction: Machine Learning Models

7.1 Source of Training Data

The study used a dataset extracted from the IHFD for training both of a regression and a classification model. As mentioned in Section 5.1, a typical patient record included 38 data fields such as gender, age, type of fracture, date of admission, time to surgery and LOS. The dataset consisted of 2,024 patient records for the year 2013.

7.2 Data Anomalies

A data anomaly was defined as an observation that appears to be inconsistent with the remainder of the dataset [33], or more generally as any data that is unsuitable for the intended use [34]. This section describes data anomalies exposed within the IHFD dataset, and the procedures conducted to deal with them.

7.3 Outlier Removal

In order to prevent the odd influence of outliers, we considered only the samples whose LOS were no longer than 40 days. The excluded outliers represented approximately 8% of the overall dataset. Figure 8 plots a histogram of the LOS used to identify the outliers.

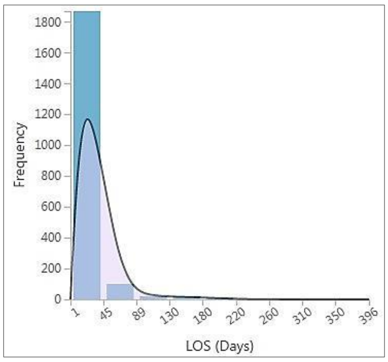
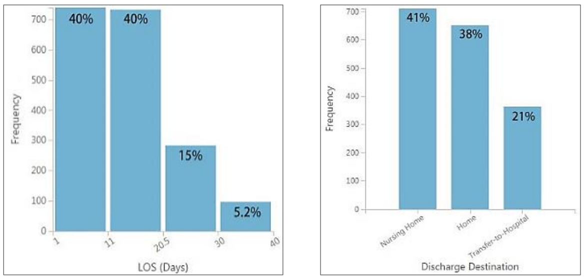


Figure 8. Histogram and probability density of the LOS variable. The outliers can be observed when the LOS becomes longer than 40 days.

7.4 Dealing with Data Imbalances

The training data was originally obtained in a form of an imbalanced dataset, which was accounted for having an adverse impact on prediction quality [35]. The problem of imbalanced data was acknowledged as one of the profound challenges in machine learning research [36]. In our case, imbalanced training samples were outstanding for inpatient LOS longer than 20 days, and discharge destinations where a patient was transferred to another acute hospital after surgery. In addition, training samples for male patients, and particular age groups were obviously underrepresented. Figure 9 shows the imbalanced histograms of the LOS and discharge destination. In order to cope with the imbalance constraint, over-sampling technique [37] was adopted. The underrepresented samples were resampled at random until they approximately contained as many examples as the other well-represented samples.



(a) (b)

Figure 9. The imbalanced training samples, where figures (a) and (b) plot histograms of inpatient LOS and discharge destination respectively.

7.5 Prediction of LOS: A Regression Model

The inpatient LOS has a pivotal importance within healthcare schemes. In addition, the LOS was recognised as the main component of the overall cost of hip fracture care [38]. A regression forest [39] model was developed to predict the inpatient LOS.

7.6 Prediction of Discharge Destination: A Multi-Class Classifier

The intuition was that a discharge destination can be predicted based on patient's characteristics and the LOS, which was predicted separately by the regression model. A random forest [39] model was developed for predicting the discharge destination.

7.7 Feature Selection

Initially, the dataset contained 38 features, however they were not all relevant. Intuitively irrelevant feature were simply excluded. In addition, the most influential features were decided based on the technique of permutation feature importance [40]. Table 6 presents the set of features used by the predictors, and their associated importance scores.

Table 6. Selected features in descending order with respect to importance score.

Predictor Model	Selected Features	
	Feature	**Importance Score ≈**
LOS Regression Model	Host Hospital	0.71
	Patient Age	0.50
	ICD Diagnosis	0.46
	Patient Residence Area	0.40
	Fracture Type	0.39
	Patient Sex	0.29
	Fragility History	0.22
Discharge Destination Classifier	Host Hospital	0.44
	Patient Age	0.35
	LOS	0.21
	Patient Residence Area	0.20
	Patient Sex	0.13

7.8 Predictors Evaluation

The predictive models were tested using a subset from the dataset described in Section 5.1. The randomly sampled test data represented approximately 40% of the overall dataset. The prediction error of each model was estimated by applying 10-fold cross-validation. Table 7 presents evaluation metrics of the LOS regression model, while Figure 10 shows the confusion matrix of the discharge destination classifier.

Table 7. Average 10-fold cross-validation accuracy of the LOS predictor.

Relative Absolute Error	Relative Squared Error	Coefficient of Determination
≈0.26	≈0.17	≈0.83

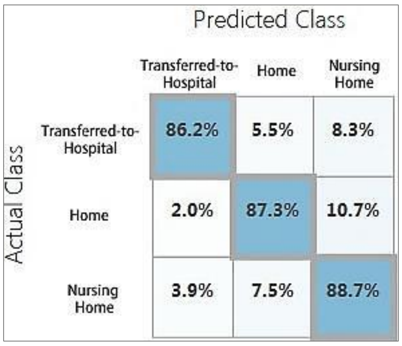


Figure 10. Average 10-fold cross-validation accuracies of discharge destination classifier.

8.0 Calculation of Cost

This section explains how the cost of treatment was calculated for every simulation-generated patient. We utilised the study [23] that provided comprehensive information on the costs within hip fracture treatment in Ireland. Generally, the cost of treatment was calculated as the equation below. Table 8 and Table 9 provide detailed information on the cost of every item.

Cost of Treatment= (ED Cost) + (Hospital Inpatient Cost) + (Outpatient Visits Cost) + (Long-Stay Care Cost)

Table 8. The description of cost assumptions.

Item	Description	Approximate Cost
ED Cost	The cost of admission to the Emergency Department	€602
Hospital Inpatient Cost	The inpatient stay at an acute hospital	According to Table 9
Outpatient Visits Cost	The cost of outpatient visits after discharge.	€154 * 9 Visits= €1386
Long-Stay Care Cost (Optional)	The cost implied by staying in long-stay care, such as nursing homes.	€700 * 32 Weeks = € 22400

Table 9. Inpatient hospital costs for patients aged 65 and over.

Age Group	Average Cost per Case (Male) €	Average Cost per Case (Female) €
65-69	7,020	5,909
70-74	8,365.64	6,353
75-79	9,249	7,879
80-84	10,418	9,376
85+	11,094	9,902

9.0 Visualisation of Results

This section aims at interpreting the results in a visual manner. All the results were obtained by averaging the outputs over 50 simulation experiments. Figure 11 shows the overall predicted cost of hip fracture treatment per year from 2016 to 2026. The cost is expected to continuously increase, and reach around 84 M by the year 2026.

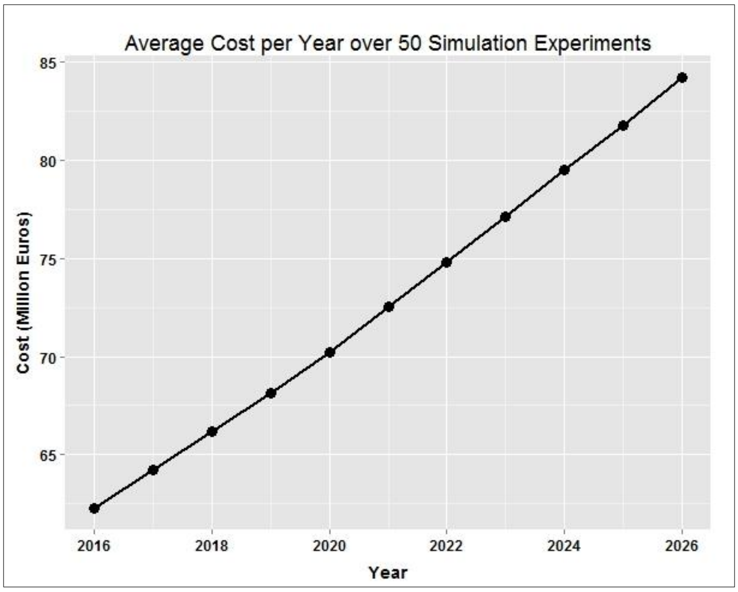


Figure 11.The average cost per year over the simulated period from 2016 to 20126. The cost was averaged over 50 simulation experiments.

Figure 12 plots the average accumulative cost for home-discharged patients compared to those who are expected to be discharged to long-stay care such as nursing homes. The figure reveals that there is a clear discrepancy between the two proportions. Though, this discrepancy agrees with that less than one-third of elderly hip-fracture patients go directly home after their hospital treatment, as reported by the HSE [15].

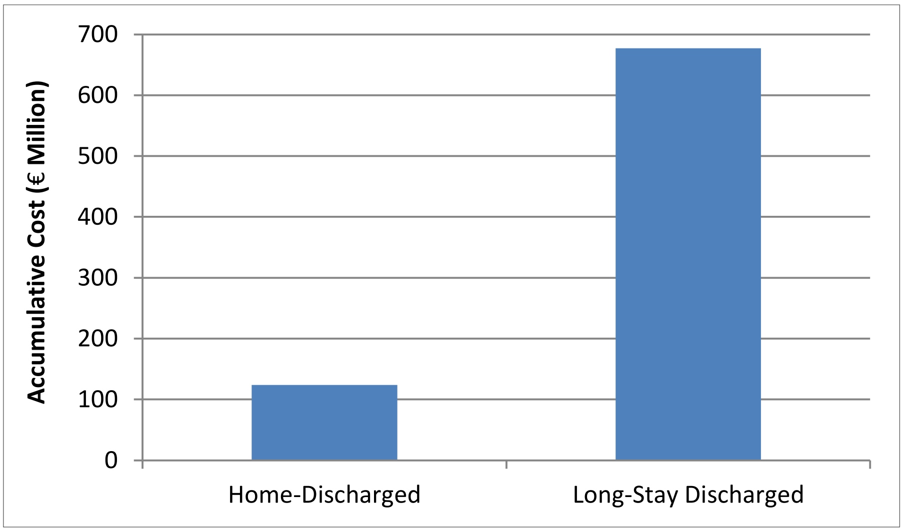


Figure 12.The average accumulative cost for home-discharged patients compared to those discharged to long-stay care.

Figure 13 refines the model results with respect to every CHO individually. Specifically, the figure plots the average accumulative cost for patients discharged to home and long-stay care within every CHO. It can be clearly observed that particular CHOs are expected to have significant higher levels of patients who are discharged to long-stay care. This prediction can be reasonable as CHO4, for example, has the highest proportion of elderly people nationwide.

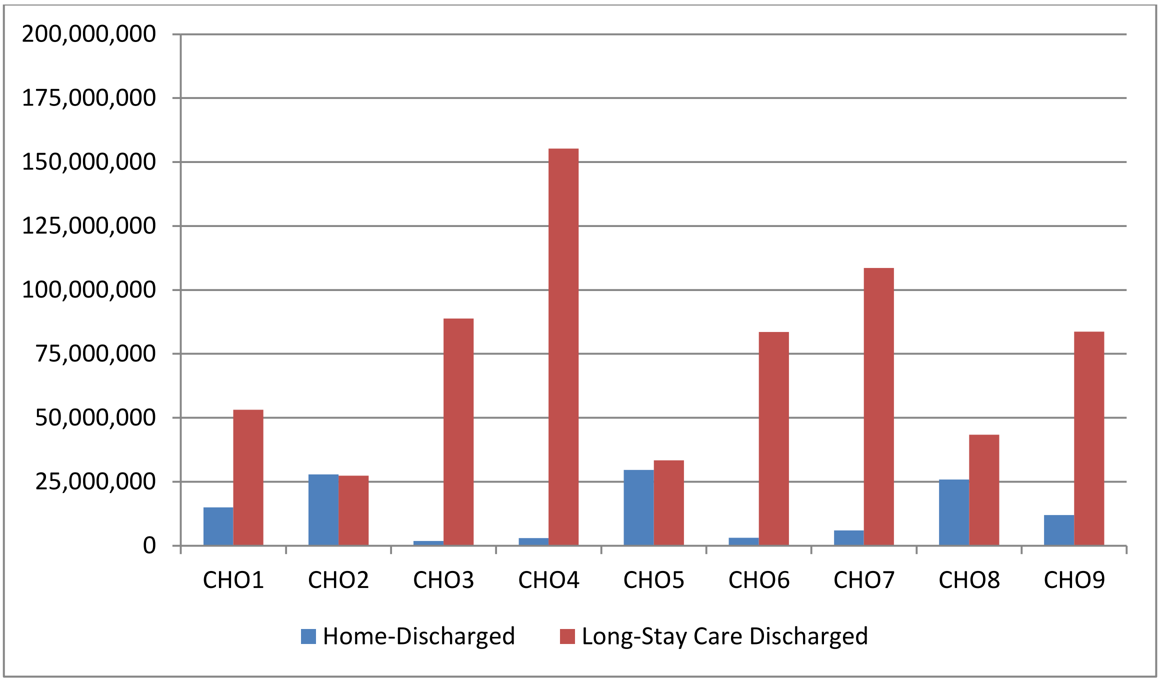


Figure 13.The average accumulative cost for home-discharged patients compared to those discharged to long-stay care in every CHO.

Figure 14 visualises a heat map of the 9 CHOs with regard to the overall predicted cost over the simulated period. The CHO4, CHO7 and CHO3 were expected to have the highest levels of costs in relation to elderly hip-fracture patients.

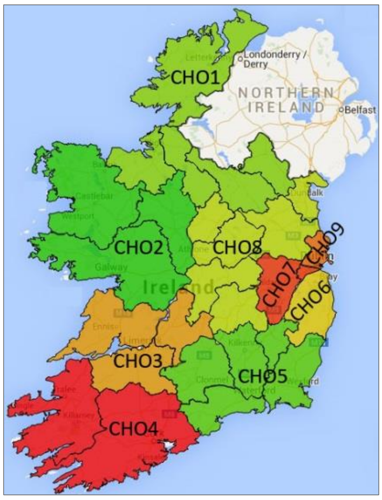


Figure 14. Heatmap: Overall predicted cost within every CHO. The predicted cost with respect to a given CHO is visually indicated by red (high) and green (low) in Figure (a).

10. Verification and Validation

10.1 Model Verification

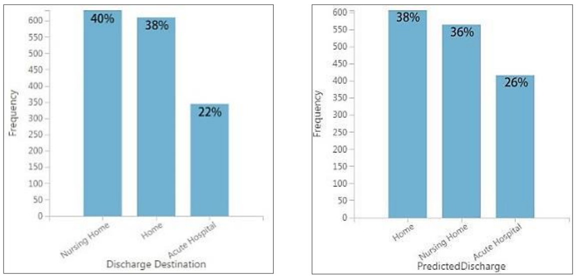
In order to examine the logic and suitability of the model, it was verified qualitatively and quantitatively. Throughout the simulation model's development, a set of verification tests [41] were conducted as follows:

- Structure-Verification Test: The model structure was checked compared to the actual system. Specifically, it was verified that the model structure reflected reality in terms of the underlying CHOs, and associated elderly populations.
- Extreme Conditions Test: The equations of the simulation model were tested in extreme conditions. For example, flows of patients were set at extreme conditions (e.g., there is no elderly population aged 60 or over).
- Parameter-Verification Test: The model parameters and their numerical values were inspected to correspond conceptually and numerically to reality. Specifically, probability distributions of patient attributes output from the model were compared against those derived from the real system, such as age, sex and fracture types for example.

10.2 Model Validation

According to [42], the most definitive test of simulation model validity is comparing outputs of the simulation model to those of the actual system. Similarly, we used the variables of discharge destination and LOS as a measure of the approximation between the simulation model and the actual system.

On one hand, Figure 15 provides a histogram-based comparison between the actual system and the simulation model regarding the discharge destination. The comparison showed that the distributions of the actual and simulated data were relatively close. However, the comparison revealed that the model slightly underestimated and over-estimated the proportion of patients discharged to long-stay care.



(a) (b)

Figure 15. Histograms of the discharge destination for the actual system and simulation model, where (a) and (b) represent the actual system and simulation model respectively.

On the other hand, Figure 16 compares the actual system's average LOS to that of the simulation model with respect to the 9 CHOs separately. The figure clearly shows that the simulated CHOs' average LOS matched the actual system very well, without any significant over- or under-estimations. Overall, validation and verification tests proved that the simulation model can be suitable for answering questions from the perspective of the study's intended objectives.

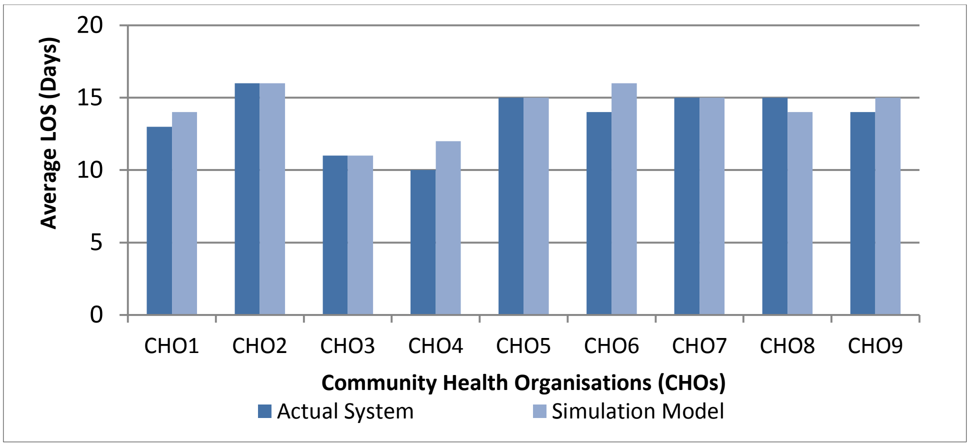


Figure 16. CHO-based comparison between the actual system and simulation model in terms of average LOS.

11. Study Limitations

- Only public acute hospitals were considered, from which the IHFD records were obtained.
- The records of the IHFD dataset did not evenly represent the 9 CHOs.
- The real data obtained by the study covered only a single year, which was 2013.
- The rate of hip fractures was assumed as a constant over the simulated interval, however it might increase or decrease in reality.
- The study considered the in-hospital cost of the patients aged 60-64 the same as 65-69, due to lack of information on this issue.
- The study did not consider other potential costs such as the ambulance costs.
- The study did not consider the indirect costs such as the quality of life.
- The study did not distinguish between the patients who are discharged to long-stay nursing homes and rehabilitation institutions, due to lack of information on rehabilitation institutions.

12. Conclusions

The significance of evidence-based decision making for healthcare has increased owing to the phenomenal challenge of population ageing. The study presented a multi-methodology approach that integrated System Dynamics with machine learning techniques. On a population basis, the SD model realised a population-based perspective of the demand for hip fracture care, regarding elderly patients in particular. On an individual patient basis, machine learning models were used to make accurate predictions on the factors that have a significant impact on the cost of treatment. Specifically, the inpatient length of stay and discharge destination were predicted for every simulation-generated patient using regression and classification models respectively. The results are articulated using a combination of domain knowledge within simulation modeling and robust data-driven prediction with machine learning.

The predicted costs are provided with reference to the geographic structure of the healthcare system in Ireland in terms of the Community Health Organisations (CHOs), whereas particular CHOs, such as CHO4 and CHO7, are predicted to experience considerable costs compared to other CHOs. The results also emphasise that the significant proportion of costs can mostly be attributed to elderly patients discharged to long-stay care facilities such as nursing homes. Generally, the study can carry useful insights for predicting the potential economic burden of elderly hip-fracture patients in Ireland.

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