HSS Journal®: The Musculoskeletal Journal of Hospital for Special Surgery
1–5

DOI: 10.1177/15563316221120582
journals.sagepub.com/home/hss
SAGE

Predicting Prolonged Hospital Stays in Elderly Patients With Hip Fractures Managed During the COVID-19 Pandemic in Chile: An Artificial Neural Networks Study

Claudio Diaz-Ledezma, MD[1,2] and Rodrigo Mardones, MD[2]

Abstract

Background: Prolonged length of stay (LOS) after a hip fracture is associated with increased mortality. *Purpose:* We sought to create a model to predict prolonged LOS in elderly Chilean patients with hip fractures managed during the COVID-19 pandemic. *Methods:* Employing an official database, we created an artificial neural network (ANN), a computational model corresponding to a subset of machine learning, to predict prolonged LOS (≥14 days) among 2686 hip fracture patients managed in 43 Chilean public hospitals during 2020. We identified 18 clinically relevant variables as potential predictors; 80% of the sample was used to train the ANN and 20% was used to test it. The performance of the ANN was evaluated via measuring its discrimination power through the area under the curve of the receiver operating characteristic curve (AUC-ROC). *Results:* Of the 2686 patients, 820 (30.2%) had prolonged LOS. In the training sample (2,125 cases), the ANN correctly classified 1,532 cases (72.09%; AUC-ROC: 0.745). In the test sample (561 cases), the ANN correctly classified 401 cases (71.48%; AUC-ROC: 0.742). The most relevant variables to predict prolonged LOS were the patient's admitting hospital (relative importance [RI]: 0.11), the patient's geographical health service providing health care (RI: 0.11), and the patient's surgery being conducted within 2 days of admission (RI: 0.10). *Conclusions:* Using national-level big data, we developed an ANN that predicted with fair accuracy prolonged LOS in elderly Chilean patients with hip fractures during the COVID-19 pandemic. The main predictors of a prolonged LOS were unrelated to the patient's individual health and concerned administrative and organizational factors.

Keywords

hip fracture, artificial intelligence, length of stay, Chile, machine learning

Received May 8, 2022. Accepted June 24, 2022.

Introduction

Hip fractures in the elderly can have an enormous social impact and represent a rising concern for health systems worldwide [6]. In Chile, 2 relevant phenomena are observed: first is that hip fracture frequency will increase during the present decade by 27.5% [7] and second is that there is a disparity in patient access to timely treatment between public and private hospitals, which has repercussions on several postoperative results, including hospital length of stay (LOS) [1]. The latter is of great relevance, since LOS beyond 14 days is associated with increased mortality rates, even when patients are satisfactorily discharged [18].

The COVID-19 pandemic and its consequences have negatively influenced the management of older adults with hip fractures [16]. On both international [21] and national levels [22], a concurrent COVID-19 infection related to an episode of hip fracture may lead to increased morbidity, prolonged LOS, and increased risk of death. Considering that the pandemic has affected all national health care systems [2], it is plausible to suggest that the LOS of patients admitted in public hospitals could have been more extended than reported [1].

Since the COVID-19 health crisis will affect our health care systems for an undetermined time, identifying the

[1]Hospital El Carmen, Santiago, Chile
[2]Clínica Las Condes, Santiago, Chile

Corresponding Author:
Claudio Diaz-Ledezma, MD, Hospital El Carmen, Avenida Rinconada 1208, Oficina 28, 5to Piso, Maipú, Santiago, Chile.
Email: claudioadiaz@gmail.com

variables associated with prolonged stays during the pandemic is paramount. Predicting episodes of prolonged LOS should help clinicians, administrators, and other health care authorities identify the factors that can be modified at the local and national levels to improve treatment outcomes of patients in Chile. Therefore, we aimed to create a prediction model of prolonged hospital stays for hip fracture episodes in the elderly Chilean population treated in public hospitals during the COVID-19 pandemic with the use of artificial neural networks (ANN).

Methods

We conducted a registry study that employed the official database of the Chilean Ministry of Health, corresponding to hospital discharges, nationally, in the year 2020. This free-access database at Fondo Nacional de Salud (https://www.fonasa.cl/sites/fonasa/datos-abiertos/bases-grd) contains de-identified records of hospital discharges from public hospitals using the international refined diagnostic related groups (IR-DRG) system. The database contains 129 columns with data pertaining to all hospital discharges (indicating demographic characteristics, procedures, comorbidities, discharge conditions, etc), including International Statistical Classification of Diseases, 10th edition (ICD-10) coding to describe diagnoses and comorbidities. The study did not require Institutional Review Board approval since the data was de-identified from a public database source.

We analyzed 80,030,631 hospital discharges from 65 Chilean hospitals for the study. Considering the 129 columns mentioned above, the total volume of potential data to be evaluated was 107,151,399 specific entries. A derived database was created, which included patients 65 years of age or older, who had as the primary diagnosis one of the following: femoral neck fracture (ICD-10 code: S72.0); pertrochanteric fracture (ICD-10 code: S72.1); or subtrochanteric fracture (ICD-10 code: S72.2). Only patients who underwent surgery and were discharged alive (to home or home hospitalization) were included. Nursing homes are not often a discharge destination in Chile, and they were not included in the present study.

Patients were excluded if they were discharged from the hospital and categorized as "deceased," discharged from the hospital without surgical intervention, or transferred from or to another hospital. The sample included all cases registered in Chile for the mentioned period. A prolonged LOS lasts more than 14 days in the context of a hip fracture in elderly patients, for the following reasons [18]:

1. It is the cutoff point associated with increased mortality in patients who are discharged to go home.
2. It is associated with a risk of 11% mortality at 30 days, which is found to be 103% higher than those discharged within 5 days.
3. The mortality risk observed in these patients is similar to those who are discharged from the hospital without surgery.

In one study [18], only 8.5% of 188,208 patients who were admitted in New York, USA, had LOS of 14 days or more. For our study, LOS of $\leq$13 days was considered "short stay" and of $\geq$14 days was "prolonged stay." The LOS was predicted as a binary variable ("short stay" or "prolonged stay"). Of the 123 variables, 18 were chosen by the authors (2 fellowship-trained adult reconstruction surgeons) due to their clinical relevance as potential predictors of prolonged LOS in hip fracture patients (Supplemental Table 1). Data were complete for each of the variables, so imputation techniques were not required [13].

Artificial neural networks (ANN) correspond to one of the subsets of machine learning, which is a branch of artificial intelligence [15]. These computational models emulate the information processing performed by the human brain. The multilayer perceptron network available in the SPSS Modeler Flow of the Watson IBM Studio commercial platform was also used. This type of neural network has one "input" layer, one "hidden" layer, and one "output" layer. It can be defined as a fully connected, feed-forward ANN with a single hidden layer. According to Greenstein et al [9], this method works by taking the input variables, multiplying them by weights (amount of impact), and using a nonlinear function to scale this information within a range. Moreover, this process occurs at each node within the neural network to optimize it (Fig. 1).

Eighty percent of the sample was used to train the model (training sample) and the remaining 20% was used to validate it (test sample). The performance of the ANN was evaluated via measuring its discrimination power through the area under the curve of the receiver operating characteristic curve (AUC-ROC). The parameters used to calculate the level of discrimination was classified as excellent (0.9–1), good (0.8–0.89), fair (0.7–0.79), poor (0.6–0.69), and failed (0.5–0.59) [11].

Results

The study comprised 2,686 cases managed in 43 public hospitals in Chile during 2020. All patients were admitted through the emergency department, underwent surgery, and were discharged alive. The average age was 81 $\pm$ 6.5 years, and 76.8% were women. In only 46 cases (2%) was the ICD-10 code U07 (diagnosis related to COVID-19 infection) listed within the first 2 comorbidities. The average hospital stay was 12 $\pm$ 9 days. We found that 443 (16.5%) underwent surgery within 2 days of admission, and 820 (30.2%) had a prolonged stay.

In the training sample (2,125 cases), the ANN correctly discriminated hospital stays in 1,532 cases (72.09%), with

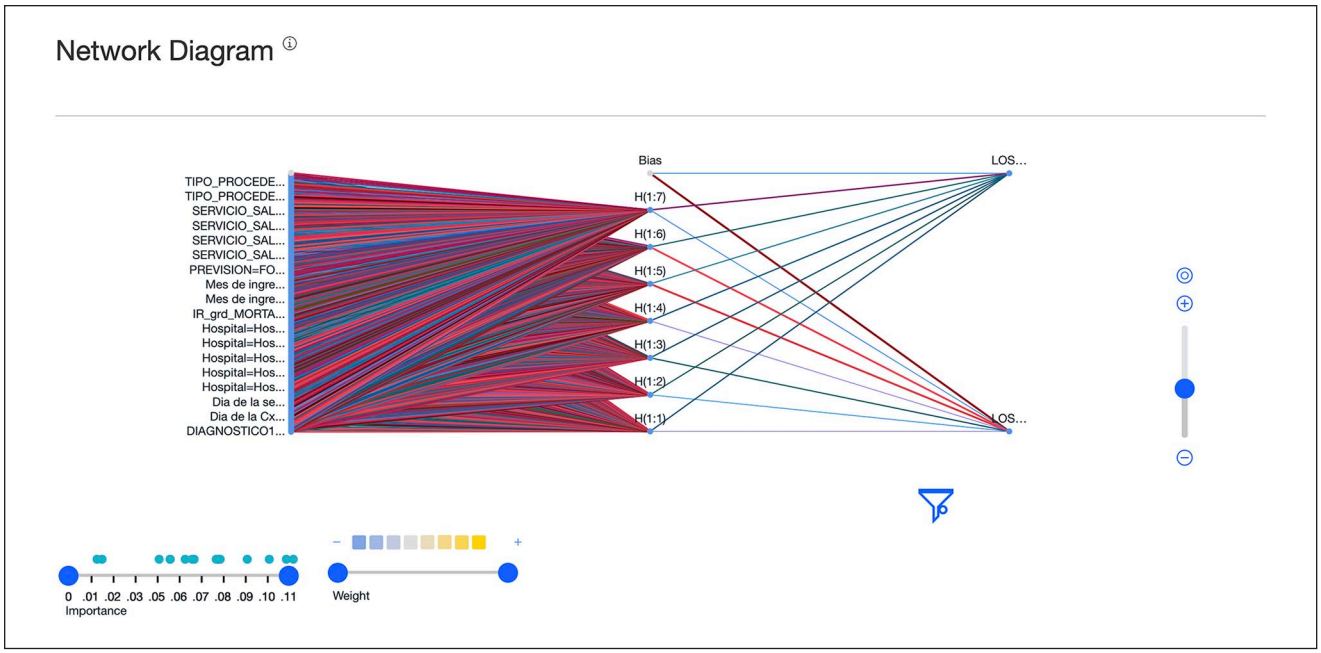

Fig. 1. Artificial neural network diagram showing the input, hidden, and output layers. The input layer shows the variables in Spanish, in the following order: origin of the patient, health service, type of insurance, month, hospital, day of the week, day of the surgery, and diagnosis. *LOS* length of stay.

AUC-ROC of .745. In the test sample (561 cases), the ANN correctly classified 401 cases (71.48%), with AUC-ROC of .742.

The ANN identified the following 6 variables with the highest relative importance in predicting a prolonged LOS (relative importance in parentheses): the hospital where the patient was managed (0.11), the geographical health service responsible for providing health care to patients according to their residential area (0.11), early surgery (or surgery performed within 2 days of admission) (0.10), IR-DRG severity level (0.09), day of the week the patient underwent surgery (0.08), and the patient's origin at the time of admission (whether the patient came from home, a local emergency department, etc.) (0.08).

This type of methodology allows the creation of different scenarios by modifying the associated variables. For example, if an 80-year-old man were hospitalized at El Carmen Hospital (in the Central Metropolitan Health Service in Santiago) with a pertrochanteric fracture (candidate for internal fixation) on a Tuesday in July, and surgery was not performed within 48 hours, he would have a 26% chance of a prolonged stay (see other possible scenarios, Supplemental Table 2).

Discussion

Employing an ANN, we developed a model to predict the risk of prolonged LOS among older adults with hip fractures during the COVID-19 pandemic in Chile. The model's capacity to predict prolonged versus short stays was found to be fair; the main predictors of a prolonged LOS were found to be organizational factors.

There are several potential limitations of our study. First, we used a public registry as a primary data source, and as with any other registry study, there is a possibility of collection and coding bias that could ultimately influence the results. However, we believe that our use of an official national database overcomes this limitation. Second, registry studies capture scarce information about patients [8], and since we included comorbidities only at 2 levels, it is possible that summarizing comorbidities through a scale such as the Charlson score [10] would have affected the results (there are no studies that validate comorbidity indexes to study episodes of hip fractures in Chile). Third, it is possible that the coding of COVID-19 during the episode of hip fracture could have been biased, considering the fact that in only 2% of the sample was COVID-19 coinfection captured in the first 2 comorbidities.

It is remarkable that in Chile during the COVID-19 pandemic there has been a low rate of early surgical resolution and a high rate of prolonged stays in comparison to international studies [18]. According to our model, the main variables that predict a prolonged LOS are organizational: (1) the hospital center where the patient was treated, (2) the health service in charge of providing health care to the patient (which is a geographical variable), and (3) the opportunity to perform an early surgery (which is understood as surgery performed within 48 hours of admission [14]). Also

relevant is that in the public health system in Chile, patients cannot choose the hospital they are admitted to. Rather, it is assigned by the health care service associated with the patient's geographic area of residence. The 3 organizational/administrative factors mentioned above are well known as a source of disparity for outcomes that are relevant in hip fracture patients. For instance, a study conducted in New York, USA, demonstrated that LOS depends on the type of hospital where the patient was managed; safety-net hospitals (those that cover uninsured or Medicaid patients) have a longer LOS compared with non-safety net hospitals [4].

The geographical region where the patient lives has also been associated with delayed surgical treatment for hip fractures in the United States [3]. This phenomenon is similar to the influence of the Health Service in our study, which is also taken as a geographical variable. In the case of Chile, even though all geographical health services depend on the Ministry of Health, economic and human resources are not equally distributed [5]. It has been proposed that the Chilean public sector is "underfunded and ill-equipped to provide care for most of the population" [5]; thus, the variation we observed may indicate disparities in access to care. Another factor that may be related to the geographical variability is the proven difference in the incidence of hip fractures by a factor of 4.5 between the regions with the highest and the lowest incidence within the Chilean territory [7], making access to care more difficult in some areas. In addition, there is evidence that surgical delay of more than 2 days depends on various administrative factors, including hospital region, admission day, and insurance type [20].

Although comorbidities were included through the ICD-10 diagnostic code at 2 levels, these were not part of the most relevant variables in our study. The IR-DRG severity level (the fourth most relevant variable in the study) is automatically calculated by the 3M IR-DRG software using the information provided by the coding personnel and could be regarded as a substitute for a comorbidity index. The ordinal values of the IR-DRG severity level represent (1) the absence of comorbidities and complications, (2) the presence of comorbidities or complications, and (3) the presence of major comorbidities or major complications. Other administrative factors relevant to our study are the day of the week the patient underwent surgery and the patient's origin (home, local emergency center) at the time of emergency admission. Both may also be related to organizational barriers.

According to Ramkumar [19], machine learning is a program that performs tasks automatically from a data source without needing explicit programming. This technology has quickly been incorporated into medical research and represents the extension of more traditional statistics. In the orthopedic literature, several recent publications have used machine learning to create prediction models for hospital stays and payments [19], probability of complications [12], postoperative satisfaction [12], and other topics. As we did in our study, all these publications use databases considered to be "big data" [17].

In conclusion, we created an ANN to predict prolonged LOS during the COVID-19 pandemic in elderly Chilean patients admitted with hip fracture. Our findings suggest an opportunity for improvement in the public sector in Chile considering that the main predictors are dependent on organizational and administrative factors.

Declaration of Conflicting Interests

The author(s) declared the following potential conflicts of interest with respect to the research, authorship, and/or publication of this article: Claudio Diaz-Ledezma, MD, reports relationships with DePuy Synthes Johnson & Johnson. Rodrigo Mardones, MD, reports relationships with Smith & Nephew.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Human/Animal Rights

All procedures followed were in accordance with the ethical standards of the responsible committee on human experimentation (institutional and national) and with the Helsinki Declaration of 1975, as revised in 2013.

Informed Consent

Informed consent was waived for all patients included in this study.

Level of Evidence

Level IV: retrospective analysis.

Required Author Forms

Disclosure forms provided by the authors are available with the online version of this article as supplemental material.

Supplemental Material

Supplemental material for this article is available online.

References

1. Barahona M, Martínez Brañes ÁJ, Rodríguez D, Barrientos C. Incidence, risk factors and case fatality rate for hip fracture in Chile: a cross-sectional study based on 2017 national registries. *Medwave*. 2020;20(5):e7939. https://doi.org/10.5867/medwave.2020.05.7939.
2. Benitez MA, Velasco C, Sequeira AR, et al. Responses to COVID-19 in five Latin American countries. *Health Policy Technol*. 2020;9(4):525–559. https://doi.org/10.1016/j.hlpt.2020.08.014.

3. Bhatti UF, Shah AA, Williams AM, et al. Delay in hip fracture repair in the elderly: a missed opportunity towards achieving better outcomes. *J Surg Res*. 2021;266:142–147. https://doi.org/10.1016/j.jss.2021.03.027.
4. Coffield E, Thirunavukkarasu S, Ho E, Munnangi S, Angus LDG. Disparities in length of stay for hip fracture treatment between patients treated in safety-net and non-safety-net hospitals. *BMC Health Serv Res*. 2020;20(1):100. https://doi.org/10.1186/s12913-020-4896-1.
5. Crispi F, Cherla A, Vivaldi EA, Mossialos E. Rebuilding the broken health contract in Chile. *Lancet*. 2020;395(10233):1342. https://doi.org/10.1016/S0140-6736(20)30228-2.
6. Curtis EM, Moon RJ, Harvey NC, Cooper C. The impact of fragility fracture and approaches to osteoporosis risk assessment worldwide. *Bone*. 2017;104:29–38. https://doi.org/10.1016/j.bone.2017.01.024.
7. Diaz-Ledezma C, Bengoa F, Dabed D, Rojas N, López A. Hip fractures in the elderly Chilean population: a projection for 2030. *Arch Osteoporos*. 2020;15(1):116. https://doi.org/10.1007/s11657-020-00794-5.
8. Grauer JN, Leopold SS. Editorial: large database studies—what they can do, what they cannot do, and which ones we will publish. *Clin Orthop Relat Res*. 2015;473(5):1537–1539. https://doi.org/10.1007/s11999-015-4223-z.
9. Greenstein AS, Teitel J, Mitten DJ, Ricciardi BF, Myers TG. An electronic medical record–based discharge disposition tool gets bundle busted: decaying relevance of clinical data accuracy in machine learning. *Arthroplast Today*. 2020;6(4):850–855. https://doi.org/10.1016/j.artd.2020.08.007.
10. Hall WH, Ramachandran R, Narayan S, Jani AB, Vijayakumar S. An electronic application for rapidly calculating Charlson comorbidity score. *BMC Cancer*. 2004;4(1):94. https://doi.org/10.1186/1471-2407-4-94.
11. Harris AHS, Kuo AC, Weng Y, et al. Can machine learning methods produce accurate and easy-to-use prediction models of 30-day complications and mortality after knee or hip arthroplasty? *Clin Orthop Relat Res*. 2019;477(2):452–460. https://doi.org/10.1097/CORR.0000000000000601.
12. Kunze KN, Polce EM, Sadauskas AJ, Levine BR. Development of machine learning algorithms to predict patient dissatisfaction after primary total knee arthroplasty. *J Arthroplasty*. 2020;35(11):3117–3122. https://doi.org/10.1016/j.arth.2020.05.061.
13. Mackinnon A. The use and reporting of multiple imputation in medical research—a review. *J Intern Med*. 2010;268(6):586–593. https://doi.org/10.1111/j.1365-2796.2010.02274.x.
14. Moja L, Piatti A, Pecoraro V, et al. Timing matters in hip fracture surgery: patients operated within 48 hours have better outcomes. A meta-analysis and meta-regression of over 190,000 patients. *PLoS ONE*. 2012;7(10):e46175. https://doi.org/10.1371/journal.pone.0046175.
15. Myers TG, Ramkumar PN, Ricciardi BF, Urish KL, Kipper J, Ketonis C. Artificial intelligence and orthopaedics: an introduction for clinicians. *J Bone Joint Surg Am*. 2020;102(9):830–840. https://doi.org/10.2106/JBJS.19.01128.
16. Narang A, Chan G, Aframian A, et al. Thirty-day mortality following surgical management of hip fractures during the COVID-19 pandemic: findings from a prospective multi-centre UK study. *Int Orthop*. 2021;45:23–31. https://doi.org/10.1007/s00264-020-04739-y.
17. National Library of Medicine. Big data. Date unknown. Available at: https://www.ncbi.nlm.nih.gov/mesh/?term=big+data. Accessed July 7, 2022.
18. Nikkel LE, Kates SL, Schreck M, et al. Length of hospital stay after hip fracture and risk of early mortality after discharge in New York state: retrospective cohort study. *BMJ*. 2015;351:h6246. https://doi.org/10.1136/bmj.h6246.
19. Ramkumar PN, Navarro SM, Haeberle HS, et al. Development and validation of a machine learning algorithm after primary total hip arthroplasty: applications to length of stay and payment models. *J Arthroplasty*. 2019;34(4):632–637. https://doi.org/10.1016/j.arth.2018.12.030.
20. Ryan DJ, Yoshihara H, Yoneoka D, Egol KA, Zuckerman JD. Delay in hip fracture surgery: an analysis of patient-specific and hospital-specific risk factors. *J Orthop Trauma*. 2015;29(8):343–348. https://doi.org/10.1097/BOT.0000000000000313.
21. Wang KC, Xiao R, Cheung ZB, Barbera JP, Forsh DA. Early mortality after hip fracture surgery in COVID-19 patients: a systematic review and meta-analysis. *J Orthop*. 2020;22:584–591. https://doi.org/10.1016/j.jor.2020.11.012.
22. Zamora T, Sandoval F, Demandes H, et al. Hip fractures in the elderly during the COVID-19 pandemic: a Latin-American perspective with a minimum 90-day follow-up. *Geriatr Orthop Surg Rehabil*. 2021;12:21514593211024508. https://doi.org/10.1177/21514593211024509.