Scala et al. BMC Public Health (2025) 25:238
https://doi.org/10.1186/s12889-025-21530-z

BMC Public Health

RESEARCH

Open Access

Use of artificial intelligence to study the hospitalization of women undergoing caesarean section

Arianna Scala[1*], Giuseppe Bifulco[1], Anna Borrelli[2], Rosanna Egidio[2], Maria Triassi[1,3] and Giovanni Improta[1,3]

Abstract

Objective The incidence of caesarean sections (CSs) has increased significantly in recent years, especially in developed countries. This study aimed to identify the factors that most influence the length of hospital stay (LOS) after a CS, using data from 9,900 women who underwent CS at the "Federico II" University Hospital of Naples between 2014 and 2021.

Methods Various artificial intelligence models were employed to analyze the relationships between the LOS and a set of independent variables, including maternal and foetal characteristics. The analysis focused on identifying the model with the best predictive performance and specific comorbidities impacting LOS.

Results A multiple linear regression model determined the highest R-value (0.815), indicating a strong correlation between the identified variables and LOS. Significant predictors of LOS included abnormal foetuses, cardiovascular disease, respiratory disorders, hypertension, haemorrhage, multiple births, preeclampsia, previous delivery complications, surgical complications, and preoperative LOS. In terms of classification models, the decision tree yielded the highest accuracy (75%).

Conclusions The study concluded that certain comorbidities, such as cardiovascular disease and preeclampsia, significantly impact LOS following a CS. These findings can assist hospital management in optimizing resource allocation and reducing costs by focusing on the most influential factors.

Keywords Caesarean section, Machine learning, Regression model, Public health, Length of stay

Introduction

Significant changes have taken place over the past thirty years concerning the method of childbirth and outcomes for newborns [1], which includes recent endeavours to decrease the high incidence of caesarean sections (CSs) [2] while simultaneously accommodating women's obstetric preferences [3, 4]. The rise in CS rates within healthcare institutions does not demonstrate any discernible overall advantages for either the infant or the mother; instead, it is connected to heightened morbidity for both parties [5]. Consequently, there is an immediate need to furnish women and healthcare providers

*Correspondence:
Arianna Scala
ariannascala7@gmail.com
[1]Department of Public Health, University of Naples Federico II, Naples 80131, Italy
[2]"Federico II" University Hospital, Naples 80131, Italy
[3]Interdepartmental Center for Research in Healthcare Management and Innovation in Healthcare (CIRMIS), University of Naples Federico II, Naples 80131, Italy

with comprehensive data regarding the possible subject risks and gains associated with caesarean delivery [5]. Despite being an invasive procedure, the rate of CS has been increasing, particularly in developed nations [6]. For example, Italy witnessed 131,390 hospitalizations for CS in 2020, marking a slight decrease compared with the previous year. For primary CS, the frequency has remained relatively stable, declining from a median value of 23.6% in 2015 to 22.0% in 2020 [7]. Among Italian regions, Campania boasts the highest CS rate, with a percentage of 58.4%. Moreover, private hospitals with fewer than 500 annual deliveries have been found to have an alarmingly high rate of 84.4% [8].

Despite ongoing efforts to reduce the CS rate, practitioners predict that there will be no significant decrease in the coming decades [9]. In fact, several legitimate reasons warrant the use of CS. Previous perineal trauma, cardiac or pulmonary conditions, placental abruption, and umbilical cord prolapse are possible factors that warrant its utilization [10–12]. Nevertheless, emerging evidence suggests that decisions may be affected by nonobstetric features [13]. For instance, psychosocial factors such as maternal concerns, media-driven fear of labor complications, and a growing preference for CS, even in the absence of medical indications, play a significant role in the increasing rates of CS. Moreover, an increasing number of older women are having their first child and the mistaken belief that the procedure is risk-free have contributed to this trend [14]. However, it is important to highlight that neither CS nor vaginal delivery is devoid of risk. Both procedures carry potential complications, and the choice between them should take into consideration not only medical but also psychosocial and personal factors. In 2010, the World Health Organization (WHO) declared that, compared with vaginal delivery, CS carries an increased risk for both the mother and the baby. Thus, a balanced and well-informed approach should be taken in determining the most appropriate mode of delivery [15].

Importantly, CS involves extended recovery periods, with women often requiring several days of hospitalization [16]. The length of hospital stay (LOS) is frequently used as a measure of healthcare quality. For example, implementing an accelerated clinical care pathway can effectively reduce LOS and associated expenses, as demonstrated in [17]. It is crucial to implement strategies for the objective study of healthcare processes [18] or to improve the management of resources in healthcare to control CAPEX costs in a modern healthcare system, which is increasingly business oriented [19–21]. However, these strategies should not only aim at optimizing hospital workflows but also enhance the efficiency of public health services by addressing the needs of local communities and ensuring equitable access to maternal care. Expenditures are related primarily to the hospital stay of different subjects (i.e., children and mothers), neonatal intensive care utilization and delivery type for some routines (e.g., childbirth) [22]. Early discharge following childbirth has become a more prevalent practice. Early discharge is defined as a hospital stay of fewer than 2 days for a natural delivery and 4 days after a CS [23]. Standardizing the LOS can not only help maintain consistent expenditure items but also increase the efficiency of the management of activities that are fundamental for elective procedures.

This study aimed to develop and evaluate artificial intelligence (AI) models for predicting the LOS for women undergoing cesarean section at the "Federico II" University Hospital. The specific objective was to identify which AI-based approaches are most effective in predicting LOS, thus providing valuable insights into healthcare quality and resource management. By accurately forecasting LOS, healthcare providers can optimize clinical workflows, enhance patient care, and ensure efficient resource allocation. The study was designed to contribute to the growing body of research exploring the application of AI in improving healthcare management and patient outcomes. By demonstrating the applicability of AI tools in maternal care, this study aims to contribute to public health by supporting data-driven decisions to optimize the allocation of resources, reduce disparities in care, and enhance the overall efficiency of healthcare systems serving diverse populations.

Materials and methods

The proposed research examined information from a cohort of 9,900 women who underwent CS at the "Federico II" University Hospital of Naples between 2014 and 2021. The data were obtained from the QuaniSDO information system, which was used to digitalize clinical records. The intervention was the CS procedure itself, and we focused on demographic information, dates of procedures, diagnoses, and the related diagnosis group (DRG).

By analysing the DRGs, the study was able to distinguish between CSs and vaginal deliveries (VDs), which served as the comparison, and possible complications in the CS routine were identified. The principal and secondary diagnoses were studied to identify significant comorbidities and conditions, leading to the division of the dataset into multiple subgroups of patients with similar conditions. The dates were used to calculate the total LOS, which served as the dependent variable, along with preoperative LOS.

Independent variables, whose distribution is shown in Fig. 1, included possible diseases and symptoms (e.g., respiratory, obesity, cardiovascular), demographic factors, preoperative LOS, and potential complications. The

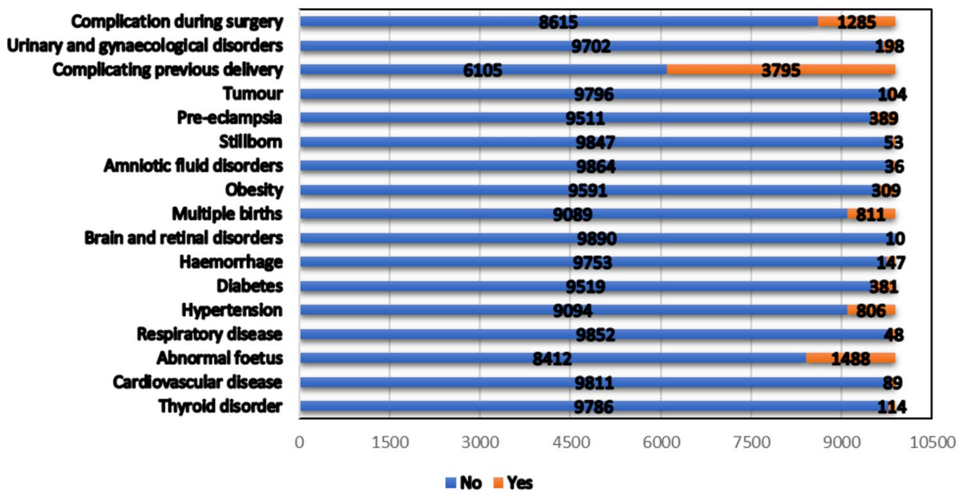

Fig. 1 Summary description of the dataset

primary outcome was the total LOS, while secondary outcomes included preoperative LOS and the presence of complications.

Regression model

We designed this model on the basis of a multistage property to improve the performance of the proposed model. Specifically, the initial step involved constructing a multiple linear regression (MLR) model **via** IBM SPSS (Statistical Package for Social Science) ver. 20. Six preliminary hypotheses were tested successively, with a particular focus on the analysis of possible linear correlations between the independent variables described in the previous section and the dependent variable (total LOS), the absence of multicollinearity, and investigation of outliers and residuals. Once we verified these assumptions, we tested other regression models that were developed in MATLAB ver. R2022a.

RF is a supervised learning model that combines multiple algorithms to improve its performance. However, there is risk of overfitting with RF models, even though they are powerful and accurate. The gradient boosted tree (GBT) is another statistical learning algorithm that is suitable for classification and regression tasks. The GBT builds a model to make decisions via a sequence of simple forecasting models, which are often based on decision trees, to improve the effectiveness through a weak learning methodology in dealing with the task by integrating their performances. The gradient-boosting (XGBoost) model was also employed for predictive regression modelling. It follows an iterative process of incorporating decision trees to improve the effectiveness of the previous approach. This approach fits models through a combination of gradient descent optimization and a loss function, aiming to diminish the loss gradient during model fitting. Logistic regression (LR) was used to determine the possible relationship between the dependent and independent variables, trained through ordinary least square methodology to estimate the coefficients on the basis of available data. Any AI-based model was analysed by considering a split of 80% (training) and 20% (test) of the entire dataset.

Classification algorithms

An alternative approach to explore the overall LOS involves the use of classification algorithms. To implement this approach, it was essential to categorize the dependent variable into distinct classes rather than treating it as a continuous variable. Based on the literature [23], the total LOS was segmented into three categories:

- Group 1: 0–4 days.
- Group 2: 5–6 days.
- Group 3: LOS > 6 days.

For implementation of this approach, the Google Colaboratory (Colab) Cloud Platform [24] was selected. The chosen classification algorithms include decision tree (DT), random forest (RF), support vector machine (SVM) and multilayer perceptron (MLP) methods.

The DT algorithm forms the foundation of the classification process and is used by more advanced models (i.e., RF) that were previously analysed. On the other hand, SVMs and MLPs employ different approaches. The SVM determines the optimal hyperplane for data separation in the classification process. Moreover, the MLP is a feed-forward neural network comprising perceptrons, which are fed as input weighted features to make the final decision on the basis of an activation function. Learning in a MLP involves adjusting these weights to minimize a specific parameter, typically the mean square error.

Table 1 The selection of hyperparameters for each algorithm

Algorithms	Hyperparameters
RF	'n_estimators': [5, 10, 15, 20], 'max_depth': [2, 5, 7, 9], cv = 10
MLP	'hidden_layer_sizes': [(50, 50, 50), (50, 100, 50), (100)], 'activation': ['tanh', 'relu'], 'solver': ['sgd', 'adam'], 'alpha': [0.0001, 0.05], 'learning_rate': ['constant', 'adaptive'], cv = 10
SVM	'kernel': ('linear', 'rbf'), 'C': [1, 10, 100], cv = 1
DT	'max_depth':range(3,20), cv = 10

For the implementation of the algorithms, we split the entire dataset into 80% (training) and 20% (test), which dynamically changes on the basis of the cross validation, implemented through the scikit-learn library, creating 10 pairs of dataset splits. This allows for the analysis of model effectiveness across different parameter sets. The performance of the models will be evaluated based on the average values obtained from these partitions.

To optimize the hyperparameters of the selected algorithms, the GridSearchCV tool was employed. This tool facilitates the adjustment of parameters specific to the dataset at hand. Table 1 presents the arbitrarily chosen parameters for the aforementioned AI models.

Results

Following the initial data pre-processing to extract the set of independent variables, we showed that the hypotheses of using MLR was verified. Specifically, we analysed the linear relationships between dependent and independent variables using relevant scatter plots. An example of such a scatter plot is shown in Fig. 2.

In this case, the scatter plot clearly demonstrates a linear relationship, which aligns with the LOS definition, although this figure does not allow evaluation of the combined effects of multiple independent features.

To assess residual independence, the Durbin−Watson test was conducted. The obtained result of 1.981 falls within the acceptable range of (1.5; 2.5) specified by the test, indicating residual independence.

To examine the constancy of variance, a scatter plot was generated, depicting the "standardized expected value regression" on the x-axis and the "standardized residual regression" on the y-axis. Figure 3 shows that the data points are randomly distributed around zero, confirming the homoscedasticity assumption.

Furthermore, we evaluated multicollinearity using two parameters (tolerance and variance inflation factor [VIF]). These parameters are based on the correlation among each independent variable. Additionally, Cook's distance was calculated for each sample to identify potential outliers that could influence the estimation of model parameters.

Table 2 confirmed that multicollinearity was missing since the variance inflation factor (VIF) and tolerance scores were consistently below 10 and above 0.2, respectively. Furthermore, Cook's distance was calculated for all 9,900 observations, and the values were found to be less than 1, ensuring the absence of outliers.

Table 3 shows the outcomes of the MLR model in terms of different metrics.

The MLR model's outstanding performance is evident even when working with a dataset comprising multiple observations and independent variables, as indicated by an R2 value surpassing the threshold of 0.5. The coefficients and results of a t test are presented in Table 4. A significance level of 0.05 was selected to identify the variables that significantly impact the output.

Table 4 highlights the variables that exert the greatest influence on the total LOS, namely, abnormal foetuses, cardiovascular disease, respiratory disorders, hypertension, haemorrhage, multiple births, preeclampsia,

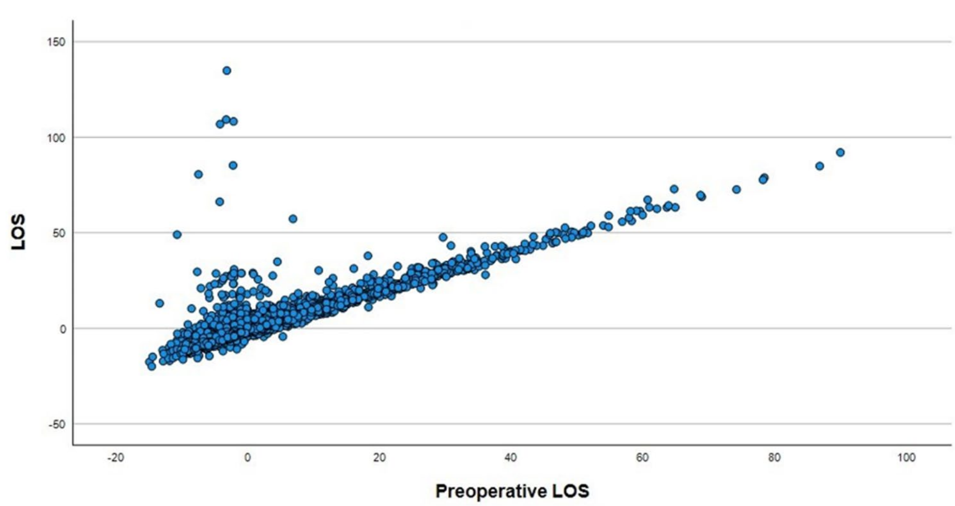

Fig. 2 Partial regression plot of the MLR model

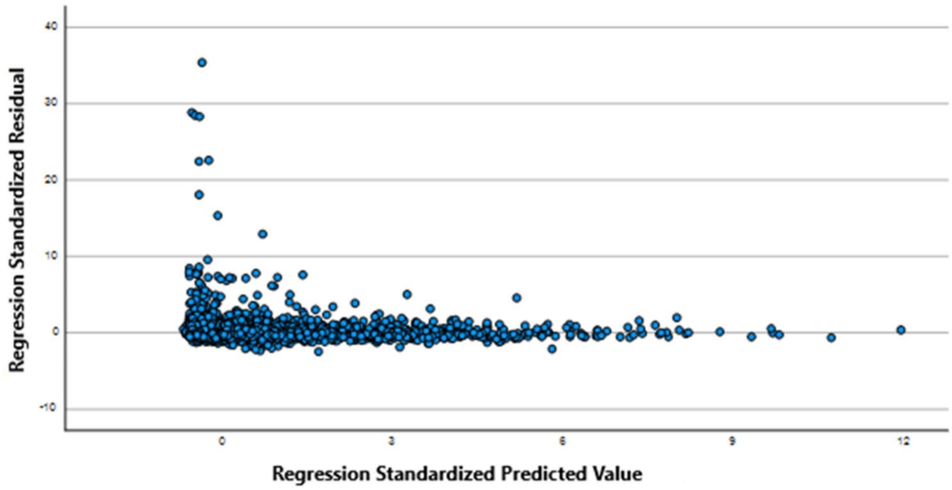

Fig. 3 Homoscedasticity of the data

Table 2 Collinearity statistics

Independent Variable	Tolerance	VIF
Age	0.972	1.029
Thyroid disorder	0.992	1.008
Cardiovascular disease	0.969	1.032
Abnormal foetus	0.943	1.061
Respiratory disease	0.958	1.044
Hypertension	0.908	1.102
Diabetes	0.829	1.206
Haemorrhage	0.974	1.027
Brain and retinal disorders	0.997	1.003
Multiple births	0.949	1.054
Obesity	0.929	1.076
Amniotic fluid disorders	0.997	1.003
Stillborn	0.997	1.003
Preeclampsia	0.901	1.110
Tumour	0.692	1.446
Complicating previous delivery	0.886	1.129
Urinary and gynaecological disorders	0.693	1.444
Complication during surgery	0.744	1.345
Preoperative LOS	0.922	1.085

complications of previous delivery, complications during surgery, and preoperative LOS.

Table 5 shows the outcomes obtained by comparing different regression models using different evaluation metrics.

Among the algorithms tested, the RF algorithm demonstrated the highest performance, achieving an R2 value of 0.813. It was closely followed by the GBT, with a score of 0.791; XGBoost, with a score of 0.787; and LR, with a score of 0.786.

Table 4 Coefficients and results of a t test for the multiple linear regression model

Variable	Unstandardized Coefficients		Standardized Coefficients	t	*p* Value
	B	Std. Error	Beta		
(Constant)	4.027	0.240		16.807	**< 0.001**
Age	0.012	0.007	0.007	1.683	0.092
Thyroid disorder	− 0.494	0.369	− 0.006	-1.337	0.181
Cardiovascular disease	− 0.849	0.422	− 0.009	-2.011	**0.044**
Abnormal foetus	0.296	0.113	0.012	2.614	**0.009**
Respiratory disease	6.843	0.577	0.052	11.858	**< 0.001**
Hypertension	0.369	0.151	0.011	2.452	**0.014**
Diabetes	− 0.066	0.224	− 0.001	− 0.294	0.769
Haemorrhage	2.252	0.329	0.030	6.851	**< 0.001**
Brain and retinal disorders	1.865	1.237	0.007	1.507	0.132
Multiple births	0.647	0.147	0.020	4.408	**< 0.001**
Obesity	0.099	0.234	0.002	0.424	0.671
Amniotic fluid disorders	0.684	0.653	0.005	1.048	0.295
Stillborn	− 0.339	0.539	− 0.003	− 0.629	0.529
Preeclampsia	1.322	0.213	0.028	6.213	**< 0.001**
Tumour	0.486	0.463	0.005	1.050	0.294
Complicating previous delivery	− 0.436	0.086	− 0.023	-5.084	**< 0.001**
Urinary and gynaecological disorders	− 0.294	0.337	− 0.005	− 0.874	0.382
Complication during surgery	0.921	0.135	0.034	6.802	**< 0.001**
Preoperative LOS	1.008	0.005	0.880	195.110	**0.000**

Table 3 Model summary

	R	R2	R2 Adjusted	RMSE	Durbin-Watson
MLR Model	0,903	0,815	0,814	3,904	1,981

Table 5 Effectiveness performance of each regression model

	RF	GBT	XGBoost	LR
R2	0.81	0.79	0.78	0.78
Root Mean Squared Error	3.853	4.124	4.139	4.142

Table 6 Accuracy and best parameters

Algorithms	Accuracy	Best Parameters
RF	0.74	'max_depth': 9, 'n_estimators': 10
MLP	0.73	'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (100), 'learning_rate': 'adaptive', 'solver': 'adam'}
SVM	0.75	'C': 100, 'kernel': 'rbf'
DT	0.75	'max_depth': 5

Table 7 Precision, recall, and F1 score of the DT algorithm

Algorithms	Class	Precision	Recall	F1-Score
DT	1	0.68	0.80	0.74
	2	0.59	0.58	0.58
	3	0.95	0.81	0.87

Table 8 Precision, recall, and F1 score of the SVM algorithm

Algorithms	Class	Precision	Recall	F1-Score
SVM	1	0.69	0.80	0.74
	2	0.58	0.59	0.58
	3	0.94	0.81	0.87

Following completion of the regression model study, we proceeded to implement classification models. The outcomes are shown in Table 6 in terms of accuracy and the related optimized parameters.

In terms of accuracy, the best algorithms are the DT and SVM algorithms. Tables 7 and 8 provide the supplementary parameters for these algorithms.

The analysis of results based on individual classes revealed that the intermediate class yielded the poorest outcomes. In contrast, class 3 exhibited favourable results. This finding holds significant importance, as class 3 represents the largest portion of the sample ($N = 4044$) and is crucial for healthcare management since it encompasses women with prolonged hospital stays. This result is further visually depicted through the ROC curves presented in Fig. 4.

As expected, the smallest region indicating the "no benefit" characteristic was specifically linked to class 2. However, both the micro- and macroaverage values were above 0.7, indicating favourable overall performance.

Discussion

This paper focuses on the analysis of data related to CS performed at the "Federico II" University Hospital. The study utilized data from the QuaniSDO information system, specifically extracting information from 9900

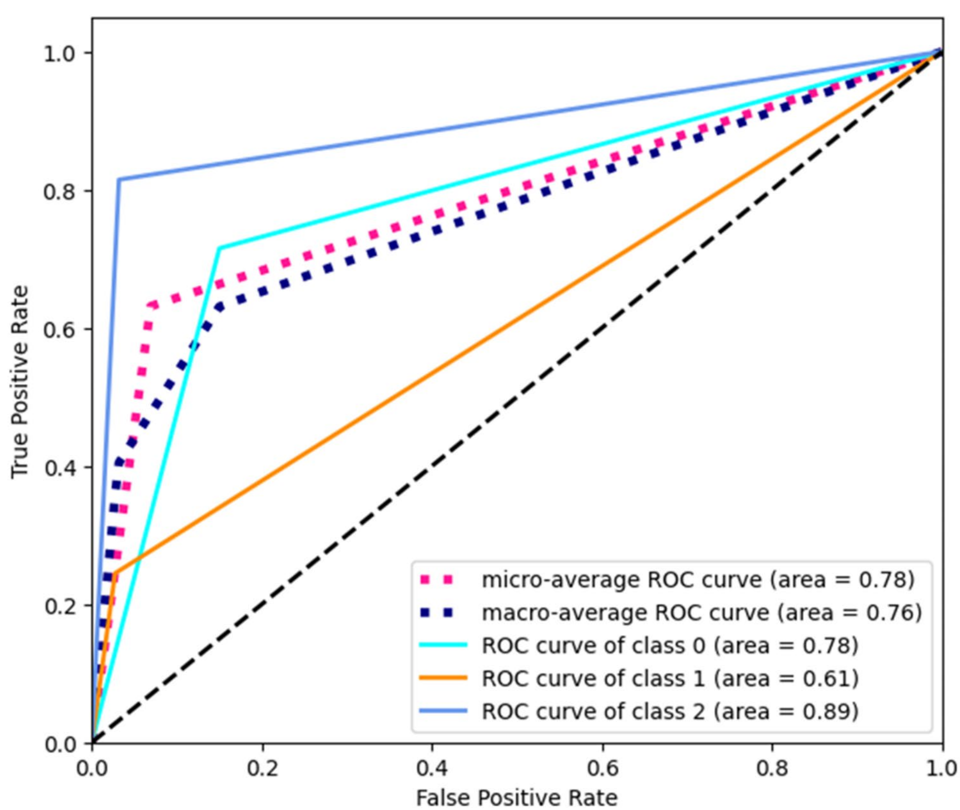

Fig. 4 ROC curves

women who underwent CS between 2014 and 2021. The dataset included variables such as age, DRG, date of admission, date of CS, and date of discharge. These variables were used to derive the dependent variable (total LOS) and independent variables (age, preoperative LOS, thyroid disorder, cardiovascular disease, abnormal fetus, respiratory disease, hypertension, diabetes, hemorrhage, brain and retinal disorders, multiple births, obesity, amniotic fluid disorders, stillborn, preeclampsia, tumor, complicating previous delivery, urinary and gynecological disorders, and complications during surgery).

An MLR model was constructed using the derived dependent and independent variables to support decision-making in health structures by estimating LOS based on an analysis of the independent variables. The resulting MLR model demonstrated a high level of performance, with an R^2 value of 0.815, making it a suitable model for data processing and prediction. Additionally, other regression algorithms were tested to expand the comparative analysis. Among these algorithms, the random forest (RF) algorithm achieves the best outcome, with an R^2 value of 0.813. However, despite RF's performance, the MLR model remained the most appropriate choice for data processing in this context, as it outperformed other algorithms.

We assessed the ability of the classification models to predict LOS classes. Among these algorithms, the decision tree (DT) and support vector machine (SVM) achieved the highest accuracy, reaching 75%. Notably, DT and SVM demonstrated excellent performance in predicting class 2, which encompasses women extending LOS, achieving F1-scores greater than 0.70.

Compared with other machine learning algorithms [25], decision trees emerged as a promising family of classifiers for various classification and regression tasks, offering effective prediction and enhanced model interpretability, particularly on large datasets. In line with our results, the authors in [26] demonstrated the application of machine learning models to clinical data, highlighting the potential of these methods in improving clinical decision-making and resource management in healthcare settings. Furthermore, our study aligns with the findings of [27], which showed the effectiveness of machine learning techniques in predicting maternal and neonatal outcomes, emphasizing the relevance of these models in obstetric care.

These findings align with those of previous studies that employed various machine learning algorithms and data-driven approaches for healthcare optimization. For example, numerous studies have utilized machine learning and AI algorithms to enhance healthcare resource management and improve predictions of clinical outcomes, including the use of Lean Six Sigma [28–31], health technology assessment [32, 33], and various machine learning algorithms [34–37] to extract valuable insights from biomedical data. Such methodologies are increasingly applied in modern healthcare systems to optimize processes, reduce costs, and enable evidence-based decision-making [38–40].

We evaluated the influence exerted by the independent variables on the dependent variable. Variables such as abnormal fetus, cardiovascular disease, respiratory disorders, hypertension, hemorrhage, multiple births, preeclampsia, complications during surgery, and preoperative LOS displayed p-values below the threshold of 0.05. While the link between preoperative LOS and LOS can be easily explained, the impact of other variables has also been highlighted in the literature. For example, the authors in [41] demonstrated the effects of multiple births and previous delivery on hospital stay for different types of cesarean sections in Italy. In [42], the authors showed that perioperative complications lead to extended hospital stays and various clinical consequences. Similarly, the study in [43] provided insights into the role of complications in extending LOS, offering a valuable comparison for our results. This work highlighted the importance of identifying critical clinical factors in predicting hospital stay and improving patient management.

The current study possesses several strengths. It includes a large number of patients and readily available clinical and demographic variables derived from hospital discharge forms. Additionally, various analysis tools were employed, enabling the understanding of clinical variables impacting LOS and providing predictive tools to assist healthcare management in planning and cost containment operations [44]. However, the study also has limitations. The dataset was not balanced regarding the presence or absence of comorbidities included in the study, and the complexity of these variables was not thoroughly discussed due to limited access to medical records. Vital signs were not included in the analysis, and as a single-center study, the results cannot be generalized to broader populations, although a similar study, which analyzed multiple years (2010–2020) and used regression and classification techniques, was conducted in another hospital in southern Italy and obtained slightly better results in terms of R^2 and accuracy [45]. As highlighted by [46], multi-center studies and the inclusion of more comprehensive data sources are essential to strengthen the generalizability of predictive models and ensure robust outcomes across different settings. This work emphasizes the value of expanding research efforts to multiple centers and incorporating additional clinical variables, such as vital signs, to enhance the predictive power of models.

Moreover, the methodologies discussed earlier in the manuscript, including the use of AI in healthcare, have been extensively studied and applied to CS and other medical procedures [47–49]. These methods offer clinicians tools to optimize healthcare processes, resource management, and decision-making based on data-driven approaches. However, it is important to note that decision tree-based models, while interpretable and useful in various contexts, have limitations compared with more sophisticated machine learning algorithms. According to [50], decision trees, although widely used, may not always be the most efficient in terms of predictive performance, particularly when applied to highly complex datasets. Future research, as noted in [46], could benefit from a multi-center approach, expanding the dataset and the range of variables considered, which would help refine the predictive models and generalize the findings beyond a single healthcare facility.

Conclusions

In this study, a thorough analysis was conducted on the data of 9,900 women who underwent CS at the "Federico II" University Hospital of Naples. We collected a set of independent variables to detail the patients' clinical conditions, enabling an examination of the total LOS. Various models, including MLR, four regression algorithms, and four classification algorithms, were tested to explore the relationships and predictive capabilities.

This application, with its relevance to healthcare management, opens several avenues for future development. In a public health context, the implementation of such AI-driven models can assist policymakers and healthcare administrators in identifying regions or populations with greater needs, supporting equitable distribution of maternal care resources, and improving the planning of healthcare interventions at a community level. First, the inclusion of VD could be considered, expanding the analysis over a longer time span and incorporating additional variables. Additionally, a combined analysis involving multiple healthcare facilities within the same territory and population area could offer further insights and a broader perspective. These findings emphasize the potential for leveraging AI not only in hospital resource optimization but also as a tool to strengthen public health strategies aimed at improving maternal and neonatal outcomes. These potential future directions would contribute to a more comprehensive understanding of the subject matter.

Author contributions

Conceptualization, A.S. and G.I.; methodology, A.S.; software, A.S.; validation, G.B., A.B. and M.T.; formal analysis, A.S.; investigation, G.I.; resources, G.B.; data curation, A.B. and G.I.; writing—original draft preparation, A.S.; writing—review and editing, R.E. and M.T.; visualization, G.B.; supervision, G.I.; project administration, G.I.; All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Data availability

The datasets generated and/or analysed during the current study are not publicly available for privacy reasons but are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

In compliance with the Declaration of Helsinki and with the Italian Legislative Decree 211/2003, Implementation of the 2001/20/CE directive, since no patients/children were involved in the study, the signed informed consent form and ethical approval are not mandatory for these types of studies. Furthermore, in compliance with the regulations of the Italian National Institute of Health, our study is not reported among those needing assessment by the Ethical Committee of the Italian National Institute of Health.

Consent for publication

Not applicable.

Consent to participate

Not applicable.

Competing interests

The authors declare no competing interests.

Received: 24 August 2023 / Accepted: 17 January 2025
Published online: 20 January 2025

References

1. Hamilton BE, Minino AM, Martin JA, Kochanek KD, Strobino DM, Guyer B. Annual summary of vital statistics: 2005. Pediatrics. 2007;119(2):345–60.
2. Althabe F, Belizán JM, Villar J, Alexander S, Bergel E, Ramos S, Kestler E. Mandatory second opinion to reduce rates of unnecessary caesarean sections in Latin America: a cluster randomised controlled trial. Lancet. 2004;363(9425):1934–40.
3. Minkoff H, Powderly K, Chervenak FA, McCullough LB. Ethical dimensions of elective primary cesarean delivery. Obstet Gynecol. 2004;104(1):193.
4. Kalish RB, McCullough L, Gupta M, Thaler HT, Chervenak FA. Intrapartum elective cesarean delivery: a previously unrecognized clinical entity. Obstet Gynecol. 2004;103(6):1137–41.
5. Villar J, Carroli G, Zavaleta N, Donner A, Wojdyla D, Faundes A, Acosta A. Maternal and neonatal individual risks and benefits associated with caesarean delivery: multicentre prospective study. BMJ. 2007;335(7628):1025.
6. McCourt C, Weaver J, Statham H, Beake S, Gamble J, Creedy DK. Elective cesarean section and decision making: a critical review of the literature. Birth. 2007;34(1):65–79.
7. pne.agenas. it [Webpage on the Internet]. Available online: https://pne.agenas.it/ (accessed on 30 December 2021).
8. Triassi M, Pugliese A, Castronuovo E, Esposito D, Passaro M. Report on the natality in Campania 2014. Napoli (IT); 2016. Italian. Available online: https://www.epicentro.iss.it/percorso-nascita/pdf/RAPPORTO%20NATALITA%202014.pdf (accessed on 1 December 2022).
9. Clapp MA, Barth WH. The future of Cesarean Delivery Rates in the United States. Clin Obstet Gynecol. 2017;60:829–39.
10. Kominiarek MA, Vanveldhuisen P, Hibbard J, Landy H, Haberman S, Learman L, et al. The maternal body mass index: a strong association with delivery route. Am J Obstet Gynecol. 2010;203:e2641–7.
11. Habiba M, Kaminshi M, Da Frè M, Marsal K, Bleker O, Librero J, et al. Caesarean section on request: a comparison of obstetricians' attitudes in eight European countries. BJOG. 2006;113:647–56.
12. Murthy K, Grobman WA, Lee TA, Holl JL. Association between rising professional liability insurance premiums and primary cesarean delivery rates. Obstet Gynecol. 2007;110:1264–9.
13. Tranquilli AL, Garzetti GG. A new ethical and clinical dilemma in obstetric practice; caesarean section `on maternal request'. American Journal of Obstetrics and Gynecology; 1997.
14. Mishanina E, Rogozinska E, Thatthi T, Uddin-Khan R, Khan KS, Meads C. Use of labour induction and risk of cesarean delivery: a systematic review and meta-analysis. CMAJ. 2014;186(9):665–73.

15. Souza JP, the WHO Global Survey on Maternal and Perinatal Health Research Group, Gülmezoglu A, Lumbiganon P, Laopaiboon M, Carroli G, Fawole B, Ruyan P. Caesarean section without medical indications is associated with an increased risk of adverse short-term maternal outcomes: the 2004–2008 WHO Global Survey on maternal and Perinatal Health. BMC Med. 2010;8:71.
16. Druzin ML, El-Sayed YY. Cesarean delivery on maternal request: wise use of finite resources? A view from the trenches. Seminars in perinatology. Volume 30. WB Saunders; 2006, October. pp. 305–8. 5.
17. Stephen AE, Berger DL. Shortened length of stay and hospital cost reduction with implementation of an accelerated clinical care pathway after elective colon resection. Surgery. 2003;133:277–82.
18. Improta G, Luciano MA, Vecchione D, Cesarelli G, Rossano L, Santalucia I, Triassi M. Management of the diabetic patient in the diagnostic care pathway. In 8th European Medical and Biological Engineering Conference: Proceedings of the EMBEC 2020, November 29–December 3, 2020 Portorož, Slovenia. Springer International Publishing; 2021, pp. 784–792.
19. Cesarelli M, Romano M, Bifulco P, Improta G, D'Addio G. An application of symbolic dynamics for FHRV assessment. In MIE; 2012 Aug. pp. 123–127.
20. Improta G, Converso G, Murino T, Gallo M, Perrone A, Romano M. Analytic hierarchy process (AHP) in dynamic configuration as a tool for health technology assessment (HTA): the case of biosensing optoelectronics in oncology. Int J Inform Technol Decis Mak. 2019;18(05):1533–50.
21. Improta G, Triassi M, Guizzi G, Santillo LC, Revetria R, Catania A, Cassettari L. An innovative contribution to health technology assessment. Modern advances in intelligent systems and tools. Berlin Heidelberg: Springer; 2012. pp. 127–31.
22. Kazandjian VA, Chaulk CP, Ogunbo S, Wicker K. Does a cesarean section delivery always cost more than a vaginal delivery? J Eval Clin Pract. 2007;13:16–20.
23. Cegolon L, Campbell O, Alberico S, Montico M, Mastrangelo G, Monasta L, Ronfani L, Barbone F. Length of stay following vaginal deliveries: a population based study in Friuli Venezia Giulia (North-eastern Italy), 2005–2015. PLoS ONE. 2019;14:e0204919.
24. Available online. https://colab.research.google.com/ (accessed on 1 June 2023).
25. Nath SS, Mishra G, Kar J, Chakraborty S, Dey N. A survey of image classification methods and techniques. In Proceedings of the 2014 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT); 2014 Jul 10–11; Kanyakumari District, India. New York City, NY, USA: IEEE; pp. 554–557.
26. Feduniw S, Golik D, Kajdy A, Pruc M, Modzelewski J, Sys D, et al. Application of artificial intelligence in screening for adverse perinatal outcomes—a systematic review. In Healthcare. 2022 Oct;10(11):2164. MDPI.
27. Olszynska A, Di Martino Z, Pawlowska A, Feduniw S, Modzelewski J, Kajdy A, et al. Epidural analgesia: effect on labor duration and delivery mode—a single-center cohort study. Ginekologia Pol. 2023;94(9):733–740.
28. Sorrentino A, Scala A, Fiorillo A, Latessa I, Abbate V, Dell'Aversana Orabona G. Six sigma approach for a first evaluation of a pharmacological therapy in tongue cancer. In 8th European Medical and Biological Engineering Conference: Proceedings of the EMBEC 2020, November 29–December 3, 2020 Portorož, Slovenia. Springer International Publishing; pp. 1028–1037.
29. Improta G, Ponsiglione AM, Scala A, Di Laura D, D'Angiolella LS, Cesarelli G. Five years of lean six Sigma in the healthcare: an overview of main tools and results. Convegno Nazionale di Bioingegneria; 2020. pp. 414–7.
30. Improta G, De Lauri C, Della Vecchia A, Borrelli A, Russo G, Triassi M. A lean six sigma approach to improve the emergency department of university hospital "San Giovanni di Dio e Ruggi d'Aragona". In 2021 International Symposium on Biomedical Engineering and Computational Biology; 2021 Aug. pp. 1–4.
31. Montella E, Marino MR, Majolo M, Raiola E, Russo G, Longo G, et al. Lean Six Sigma approach to the study of the LOS of patients who undergo laparoscopic cholecystectomy: a bicentric study. In Proceedings of the 6th International Conference on Medical and Health Informatics; 2022 May pp. 247–252.
32. Improta G, Simone T, Bracale M. HTA (Health Technology Assessment): a means to reach governance goals and to guide health politics on the topic of clinical risk management. World Congress on Medical Physics and Biomedical Engineering, September 7–12, 2009, Munich, Germany: Vol. 25/12 general subjects. Berlin Heidelberg: Springer; 2009. pp. 166–9.
33. Krubiner CB, Tugendhaft A, DiStefano MJ, Barsdorf NW, Merritt MW, Goldstein SJ, et al. The value of explicit, deliberative, and context-specified ethics analysis for health technology assessment: evidence from a novel approach piloted in South Africa. Value in Health Reg Issues. 2023;34:23–30.
34. Picone I, Latessa I, Fiorillo A, Scala A, Trunfio A, Triassi M. Predicting length of stay using regression and Machine Learning models in Intensive Care Unit: a pilot study. In 2021 11th international conference on biomedical engineering and technology; 2021 Mar. pp. 52–58.
35. Marino MR, Borrelli A, Rubba F, Triassi M, Improta G. Advanced Data Analysis Techniques to Study Valvuloplasty Hospitalization: A Multicenter Study. In International Conference on Biomedical Engineering of the Universiti Malaysia Perlis; 2023 Sep. Cham: Springer Nature Switzerland; pp. 248–255.
36. Marino MR, Longo G, Triassi M, Improta G. Use of machine learning algorithms to study the impact of COVID-19 in surgical departments of University Hospital "Federico II". In International Conference on Biomedical Engineering of the Universiti Malaysia Perlis; 2023 Sep. Cham: Springer Nature Switzerland; pp. 364–372.
37. Ponsiglione AM, Zaffino P, Ricciardi C, Di Laura D, Spadea MF, De Tomasi G, et al. Combining simulation models and machine learning in healthcare management: strategies and applications. Prog Biomed Eng. 2024;6(2):022001.
38. Trunfio TA, Improta G. Flow Analysis of Mastectomy patients using length of Stay: a single-center study. BioMedInformatics. 2024;4(3):1725–44.
39. Loperto I, Scala A, Rossano L, Carrano R, Federico S, Triassi M, Improta G. Use of regression models to predict glomerular filtration rate in kidney transplanted patients. In 2021 International Symposium on Biomedical Engineering and Computational Biology; 2021 Aug. pp. 1–4.
40. Marino MR, Trunfio TA, Ponsiglione AM, Amato F, Improta G. Investigation of emergency department abandonment rates using machine learning algorithms in a single centre study. Sci Rep. 2024;14(1):19513.
41. Cegolon L, Mastrangelo G, Maso G, Pozzo GD, Heymann WC, Ronfani L, Barbone F. Determinants of length of stay after cesarean sections in the Friuli Venezia Giulia region (north-eastern Italy), 2005–2015. Sci Rep. 2020;10:19238.
42. El-Sayed YY, Lyell DJ, Nelson LM, Butwick AJ, Blumenfeld YJ. Risk factors for prolonged postpartum length of stay following cesarean delivery. Am J Perinatol. 2015;32:825–32.
43. Kajdy A, Sys D, Modzelewski J, Bogusławska J, Cymbaluk-Płoska A, Kwiatkowska E, et al. Evidence of Placental Aging in Late SGA, fetal growth restriction and stillbirth—a systematic review. Biomedicines. 2023;11(7):1785.
44. He Z, Cheng Z, Wu T, Zhou Y, Chen J, Fu Q, Feng Z. The costs and their determinant of cesarean section and vaginal delivery: An exploratory study in Chongqing Municipality, China. BioMed Res Int. 2016;2016:1–9.
45. Ponsiglione AM, Trunfio TA, Amato F, Improta G. Predictive Analysis of Hospital Stay after caesarean section: a single-center study. Bioengineering. 2023;10(4):440.
46. Feduniw S, Kajdy A, Sys D, Malinowska O, Wieczorek K, Bagińska K, Baranowska B. Did everyone change their childbirth plans due to the COVID-19 pandemic?A web-based cross-sectional survey of Polish pregnant women. Journal of Advanced Nursing. 2023;79(7):2664–2674.
47. Chai Z-Y, Hu H-M, Ren X-L, Zeng B-J, Zheng L-Z, Qi F. Applying lean six Sigma methodology to reduce cesarean section rate. J Eval Clin Pract. 2016;23:562–6.
48. Verhoeven CJ, Oudenaarden A, Hermus MA, Porath MM, Oei SG, Mol BW. J. Validation of models that predict cesarean section after induction of labor. Ultrasound Obstet Gynecol off J Int Soc Ultrasound Obstet Gynecol. 2009;34:316–21.
49. Deng B, Li Y, Chen J-Y, Guo J, Tan J, Yang Y, Liu N. Prediction models of vaginal birth after cesarean delivery: a systematic review. Int J Nurs Stud. 2022;135:104359.
50. Charbuty B, Abdulazeez A. Classification based on decision tree algorithm for machine learning. J Appl Sci Technol Trends. 2021;2(01):20–8.

Publisher's note