Association between the severity of dysphagia and its determining factors

Original Article

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Abstract

Objectives: characterize, in a sociodemographic and clinical perspective, pacients who underwent videoendoscopy of swallowing and had oropharyngeal dysphagia during their hospital stay. Furthermore, it is also intended to find strategies to improve the quality of the response to pacientes in need of videoendoscopy of swallowing.
Case study: this study is based on a sample collected in Centro Hospitalar Universitário Santo António, between january 2019 and september 2021, including.
Materials and Methods: the clinical data and image studies from 157 pacients were retrospectively analyzed. After careful selection, all cases that did not meet the inclusion criteria were excluded from the study. Thus, 143 patients were selected for analysis.
Results and conclusions: this study identifies determining factors of FOIS level variability, detecting severe patients in a preliminary, pre-VED phase, reducing waiting time by over 70%, and consequently improving service quality in all its dimensions.

Keywords: Oropharyngeal dysphagia; Video-endoscopy of swallowing; Machine learning; Costs

Introduction

Swallowing is one of the most primitive and vital physiological processes in humans, which involves the movement of liquid or solid substances from the oral cavity to the stomach. This complex process requires the coordination of numerous anatomical, neural, and muscular structures of the respiratory, oropharyngeal, and gastrointestinal systems to occur effectively and safely. The underlying physiology of swallowing comprises three sequential phases: oral, pharyngeal, and esophageal.[1,2]

Oropharyngeal dysphagia

The presence of underlying pathologies due to aging or neurological, mechanical,

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or iatrogenic causes can affect one or more phases of the swallowing mechanism, resulting in dysphagia - a difficulty in moving food into the stomach. Dysphagia is classified as oropharyngeal or esophageal, depending on the affected site. This study focuses exclusively on oropharyngeal dysphagia (OD). OD presents with varied symptoms, ranging from difficulty in initiating swallowing to the complete inability to swallow saliva or food of different consistencies.[1,2] Patients with dysphagia should undergo a systematic and detailed anamnesis, particularly with regard to the progression of the current disease and medical history. Although the objective examination is not specifically aimed at addressing dysphagia, it should focus on identifying the underlying diseases (neuromuscular, digestive, and connective tissue) and warning signs.[1-3]

Endoscopic evaluation of swallowing

Patients with dysphagia should undergo both a clinical and instrumental evaluation. Fiber-optic endoscopic evaluation of swallowing (FEES) is a complementary diagnostic test that enables anatomical and functional assessment of the oropharyngeal system, providing an instrumental evaluation of swallowing.[1,4]

FEES is one of the gold standard methods for evaluating and diagnosing OD, along with videofluoroscopy (VFC). Some of the advantages of FEES include absence of radiation, portability, and visualization of non-radiopaque secretions.[1,4] It is a useful, safe, and inexpensive procedure that can be widely used in daily clinical practice for patients of all ages. Potential adverse events include epistaxis, vasovagal syncope, and laryngospasm, each occurring in less than 2% of patients. Several studies, involving thousands of patients, have reported self-limited complications that resolved without sequelae, although the test may cause discomfort to patients.[5,6]

Functional oral intake scale (FOIS)

Several international scales can be used to evaluate and screen dysphagia, including the Mann Assessment of Swallowing Ability,7 Clinical Dysphagia Scale,[8] Penetration Aspiration Scale,[9] and FOIS.[10] The FOIS was developed in 2005 and is a highly reliable, valid, and sensitive tool for objectively determining and monitoring the oral intake range of patients with OD. This ordinal scale classifies the oral intake of solid and liquid foods into seven levels and is the most widely used method for classifying patients with OD in both clinical and research settings. This scale is simple and reproducible, and enables a quick assessment of the degree of swallowing impairment. It supports an individualized therapeutic approach aimed at preventing more serious complications.[1,11,12]

Study relevance and objectives

Hospital services are under increasing pressure to provide effective, efficient, and affordable health care. Previous studies have reported an increase of approximately 40% in hospital costs due to OD.[13] This study aimed to characterize the patients undergoing FEES who experienced OD during the hospitalization period, along with evaluating the sociodemographic and clinical parameters. Additionally, we sought to identify strategies to improve the response time to patients requiring FEES. The study sample was collected at the Centro Hospitalar Universitário Santo António between January 2019 and September 2021.

Materials and methods

A retrospective analysis of the medical records and imaging reports of 157 inpatients at the Centro Hospitalar Universitário Santo António, who underwent FEES between January 2019 and September 2021 was performed. The same physician conducted or directly supervised all the tests. After careful selection, 13 patients were excluded for refusing to collaborate and one was excluded for not having clinical OD. Thus, the final sample comprised 143 patients.

Analyzed parameters

Data were collected from the electronic medical records of patients at the Centro Hospitalar Universitário Santo António using the SClínico software. The demographic data of the patients included sex, age, reason for hospitalization, relevant personal history to characterize the risk factors for dysphagia (surgery, radiotherapy [RT], structural disorders of the head and neck, or neurological and metabolic diseases), feeding methods (oral or alternative), date of FEES request and examination, referral service, FOIS classification, number of hospitalization days until request, and date of death (if applicable). The parameter "reason for hospitalization" included 77 categories, which were grouped by the physiological system due to the small sample size (143 patients). For example, the categories "ischemic stroke" and "hemorrhagic stroke" were grouped into "neurological."

In this study, the target parameter was the FOIS classification, which defines the severity of the disease. The FOIS is determined by FEES, which can be uncomfortable for the patient, burdensome for the hospital due to the increased length of hospital stay, and subject to a queue of several days because of demand overload. The aim of this study was to predict the severity of dysphagia at admission based on the patient's medical history, thereby preventing unnecessary FEES in non-severe patients. We expect this approach to reduce the number of FEES requests, consequently decreasing the queueing period.

Statistical analysis

All data were anonymized, and statistical analysis was performed using Microsoft Excel, IBM SPSS Statistics version 26, and Waikato Environment for Knowledge Analysis (Weka) version 3.8.6. Weka was used to analyze and process statistical data. It includes a pre-defined set of machine learning algorithms that help to manipulate datasets and generate and explore classification models, among other functions.[14] Summary measures of the variables were presented according to their type and distribution.

Machine learning

Recognizing that the analyzed parameters and FOIS level may follow a pattern raises the question: Is it possible to predict a patient's FOIS level at an early stage to detect and differentiate serious OD cases from others?

We studied machine learning methods to evaluate the hypothesis that it is possible to detect severe OD cases at an early stage,15 particularly their classification. The aim was to predict the FOIS level of a patient presenting with a clinical condition, based on the parameters analyzed during the medical appointment (signs, symptoms, and history).

Machine learning uses data to identify patterns and construct models for predicting behaviors and outcomes in circumstances identical to those described by the data.[15] Classification is one of the problems that can be solved using machine learning. It consists of determining the class or category of an observation described by a set of parameters. The classifier (or classification model) can be learned based on a set of observations in which the class of each individual is previously known, which is called supervised classification.[16] A constructed classifier can then be applied to new cases to predict their class. The quality of a classification model depends on the volume of the training data available: a greater volume of data provides more evidence about the phenomenon analyzed, usually producing more accurate models. A classification model can be reconstructed at any time to incorporate new data.

FOIS level prediction

The search for a model to evaluate our hypothesis began by exploring the data as provided, using the simplest and least demanding models. This is a common procedure in machine learning, representing the heuristic research principle, which states that among several possible alternative explanations for a phenomenon, the simplest one should be chosen.[15] Subsequently, we implemented an iterative process that generated and analyzed a classifier at each iteration to identify a model with reasonable predictive capacity. The generated classifiers utilized variable algorithms and different data organization formats.

Queueing theory

The queueing theory17 provides a set of analytical models that can be applied to general situations and modeled by queueing systems, such as in the case of FEES. These models estimate the average queueing time per patient based on the characteristics of the system, the arrival rate (average number of patients using this service), and server/physician occupancy rate (percentage of time during which the physician is engaged in providing the service). For this estimation, we assumed that a physician has an occupancy rate of 90% and used the M/M/1 analytical model, which works with a single queue and single server.[18]

Results

Descriptive analysis

The sample comprised a total of 143 patients undergoing FEES. At the time of data collection, 64 patients (44.6%) had died.

The participants' medical records showed that nine patients (6.3%) had undergone head and neck RT, 34 (23.8%) had undergone head and neck surgery, 96 (67.1%) had a history of metabolic disorders, 70 (49.0%) had a history of neurological disorders, and 13 (9.1%) had a history structural disorders. Among the metabolic disorders, there were 89 (62.2% of the study sample) cases of hypertension (HTN) and 43 (30.1% of the study sample) cases of diabetes mellitus (DM). Among the patients with a history of metabolic disorders, 30 (31.3%) had both HTN and DM. Structural disorders included six (4.2%) cases of head and neck neoplasms, three (2.1%) cases of facial trauma, and four (2.8%) cases of vocal fold pathology. Among the patients with structural disorders, 46.2% had a previous diagnosis of neoplasia. We also analyzed the history of neurological disorders, including significant risk factors for the onset of OD, and identified 65 (45.5%) patients with six highly-prevalent diseases and five patients with other pathologies. Approximately 50% of these patients had a history of stroke. In-hospital progression was analyzed based on reason for hospitalization, length of hospital stay, feeding method, and the service that referred the patient for FEES. The most frequent reasons for hospitalization were pulmonary (n = 38, 26.6%) and neurological (n = 33, 23.1%) conditions, which together accounted for approximately 50% of all cases. Among the 14 categories of reasons hospitalization, the six most prevalent ones corresponded to more than 80% of cases of OD.

The FOIS is an ordinal scale with seven levels. Levels 1–3 correspond to tube-dependent feeding, such as a nasogastric tube (NGT) or percutaneous endoscopic gastrostomy (PEG). Levels 4–7 describe different degrees of oral feeding, including dietary modifications and compensatory procedures such as liquid food restrictions and prolonged meal periods.[7]

The data were subjected to principal component analysis to identify the parameters that explained the FOIS level variability in the sample.[19] The analysis revealed that a linear combination of the parameters of RT, history of structural disorders, and surgical history explained 17.3% of this variability.

FOIS level prediction

The first classification model generated was based on the observed data without any pre-processing, as presented in the Descriptive Analysis section. This model had an accuracy

Table 1
Sociodemographic data

Sample	N	Age (years)		
		Minimum	Maximum	Average
Male	100 (69,9%)	25	94	70,4 ± 13,7
Female	43 (30,1%)			

The sample comprised 30.1% females and 69.9% males. The average age was 70.4 ± 13.7 years, ranging between 25–94 years.

Table 2
In-hospital progression

Days	Minimum	Maximum	Average
Admissions	1	132	31,6 ± 26,4
From request to examination (FEES)	0	252	10,6 ± 23,6

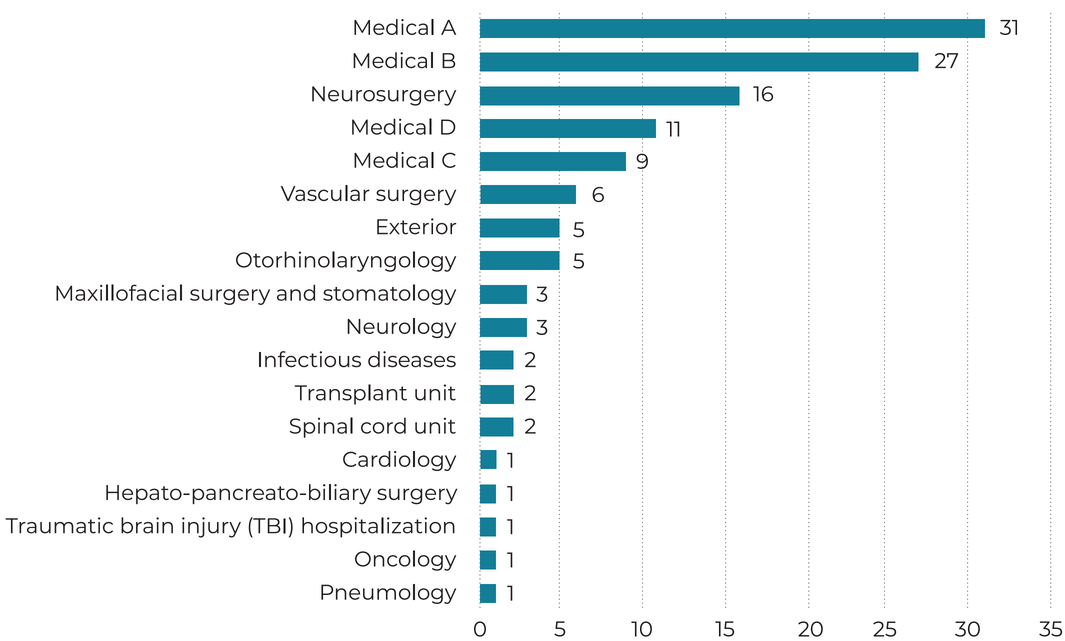
The average length of hospital stay was 31.6 days, ranging between 1–132 days. The queueing time for the test averaged 10.6 days, but a severe outlier with no causality was identified, which is discussed in the queueing time estimation section.
FEES, Fiber-optic endoscopic evaluation of swallowing.

Table 3
Feeding method

Feeding	N	%
Oral	92	64,3%
Nasogastric tube	46	32,3%
Percutaneous endoscopic gastrostomy	4	2,8%
Nasojejunal tube	1	0,7%

Approximately 2/3 of the patients were fed orally, four underwent percutaneous endoscopic gastrostomy (PEG), and one used a nasojejunal tube (NJT). Approximately 1/3 of the patients used a nasogastric tube (NGT) (n = 46, 32.2%).

Figure 1
Referral services



Medical and neurosurgery units accounted for 65.8% of referrals for FEES.

rate of 25.3%, indicating that it accurately predicted the FOIS level for one in every four patients in the sample. It is considered a trivial model because it always predicts the most frequent class - FOIS 1 - with a relative frequency of 25%. We tried to increase the accuracy rate with several classification models, including decision rules, decision trees, instance-based learning models, probabilistic models, and neural networks.[14] However, the accuracy rate

Table 4
Dysphagia evaluation

FOIS	N	%	Median	Mode
1	36	25,2	4	1
2	9	6,3		
3	9	6,3		
4	24	16,8		
5	33	23,1		
6	26	18,2		
7	6	4,2		

The most prevalent FOIS levels were F1 and F5, each corresponding to more than 20% of the sample, respectively: 25.2% (n = 36) and 23.1% (n = 33). They were followed by F6 (18.2%, n = 26) and F4 (16.8%, n = 24). In total, these four levels corresponded to 83.3% of the sample. All the other levels had a relative frequency below 7%.

never reached a satisfactory level. The small sample size for machine learning purposes (143 cases and seven classes) may have significantly influenced the results. These conditions can often lead to overfitting,[20] which occurs when the generated model replicates the training data set but fails to generalize the results for predicting the class of new individuals.

In the second phase, we modified the explanatory variables to reduce the noise that might have been generated by excessive details in a small sample. For example, "age," which was a numerical variable ranging between 25–94 years, was transformed into a binary variable (< 50 and ≥ 50 years). The variables were artificially modified but based on the most current evidence on the risk factors for OD.[1,12,21–24]

The subsequent strategy was also modified. Instead of trying to predict the FOIS level, we focused on identifying the patients that were potentially susceptible to developing serious complications. Therefore, a new target parameter grouped the FOIS levels into two classes: F1–3, consisting of FOIS levels 1, 2, and 3; and F4–7, comprising the other levels.

These alterations resulted in the JRIP model (decision rules), which can differentiate between these two classes with an accuracy of 65.7%. However, the benefits of this model are small compared to the trivial model, since a model that always predicts the largest class has an accuracy of 62%.

Classification based on linear regression was slightly more accurate than the JRIP model, reaching an accuracy of 66.4%, making it the model with the best accuracy rate.

However, both models had a significant percentage of false negatives (FN), which should be prevented. The JRIP model classified 26 of the 54 patients with FOIS levels between 1–3 as F4–7, while the classifier based on linear regression incorrectly classified 31 patients as F4–7. Finally, knowing beforehand that a reduced number of FN could affect the overall accuracy, we prioritized minimizing FN to ensure early detection of patients meeting the severity criteria. From this perspective, it is preferable to classify a patient not meeting the severity criteria as severe rather than failing to diagnose a patient with severe disease, since this patient will undergo FEES, and the initial suspicion will not be confirmed. We reduced the number of FN by generating a model (Figure 2) that penalizes FN with a higher weight than false positives. After testing various values, we selected a 2:1 ratio. This model achieved an accuracy rate of 47.6%, with only six FN, thereby reducing the number of FN by 76.9%. All evaluated classifiers considered the parameters of previous RT, structural disorders, and history of surgical disorders. A confusion matrix (Table 5) was used to assess the performance of the classifiers.

Figure 2
Weka output cost-sensitive classifier

```
Evaluation cost matrix:
 0 1
 2 0


=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          68               47.5524 %
Incorrectly Classified Instances        75               52.4476 %
Kappa statistic                          0.0924
Total Cost                              81
Average Cost                             0.5664
Mean absolute error                      0.5207
Root mean squared error                  0.5602
Relative absolute error                110.6406 %
Root relative squared error            115.5246 %
Total Number of Instances              143

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.225    0.111    0.769      0.225    0.348      0.143    ?         ?         f4-7
                 0.889    0.775    0.410      0.889    0.561      0.143    ?         ?         f1-3
Weighted Avg.    0.476    0.362    0.634      0.476    0.428      0.143    ?         ?

=== Confusion Matrix ===

  a  b   <-- classified as
 20 69 |  a = f4-7
  6 48 |  b = f1-3
```

The cost evaluation matrix indicates that the objective was to generate a model that penalizes false negatives, i.e., F1–3 cases (severe patients) classified as F4–7 (non-severe patients), thus reducing the number of severely ill patients that were incorrectly classified.

Queueing time estimation

The distribution of the response time between the FEES request and examination was skewed to the right (coefficient of skewness of 8.2), with a mode of four, median of six, and mean of 10.6 days. The first quartile was four days, and the third quartile was nine days. The most extreme severe superior outlier was a patient with a response time of 252 days due to clinical worsening to the point of being hemodynamically unstable for the procedure. When this outlier was excluded, the mean response time was 8.9 days, decreasing the bias (coefficient of skewness of 4.9).

According to the theory of queueing, the average queueing time was estimated to decrease from 8.9 to 2.3 days, representing a reduction of 74.2% (Equation 1). Figure 2 is a schematic representation of the following two situations: (1) 100% of patients undergo FEES, or (2) only patients identified as severe by the classification algorithm undergo FEES.

Discussion

Some studies have suggested that the patient's age and medical history are critical in determining the approach to OD, particularly with regard to the neurological and iatrogenic history. Swallowing disorders have an incidence of 16–22% in individuals over 50 years of age, reaching 70–90% in patients over 70 years of age. Studies have indicated a higher prevalence in men compared to women, with a ratio of 1.5:1.1 Stroke is one of

Table 5
Confusion matrix

Observed / Predicted	F4-7	F1-3
F4-7	A	B
F1-3	C	D

A confusion matrix is a table with two inputs: observed and predicted target parameter values, which in this case was the FOIS level. Table 5 shows the observed classes: the first row presents the F4–F7 FOIS levels and the second row presents the F1–3 FOIS levels. The columns correspond to the predicted classes, with cell A containing the number of F4–7 cases that the classifier identified as F4–7, i.e., true positives. In general, the main diagonal of a confusion matrix contains the true positives from each of the classes. The other cells correspond to cases that were wrongly classified. Cell C presents F1–3 false negatives, which should be reduced.

the comorbidities most strongly correlated with OD, with approximately 76% of post-stroke patients experiencing dysphagia.21,22 Aspiration is a common and potentially severe complication that can affect up to 55% of these patients.[21] The early detection of OD is particularly important,[1,25] but a definitive diagnosis requires additional tests such as FEES, which is available at the Centro Hospitalar Universitário Santo António. The evaluation of OD using FEES is still in its early stages, with a limited amount of literature available. This study aimed to identify the factors associated with the onset of dysphagia and prediction of clinical severity.

Our findings on the population characteristics of OD corroborate with the findings in the literature. The average age of the participants in this study (70.4 years) aligns with the age of peak onset of OD, which typically starts in the seventh decade of life. Regarding the distribution by sex, our results confirm a higher incidence of dysphagia in men than in women, with a ratio of 2.3:1. As stated earlier, the main comorbidities associated with OD have neurological and iatrogenic etiologies. Approximately one-fourth of our sample had a history of stroke. Head and neck surgery was also a determinant for the onset of dysphagia, having been performed in 23.8% of our patients. The results of this study are consistent with those of previous studies, which reported a higher incidence of OD in older, male patients with a neurological or iatrogenic history of head and neck disorders, thus validating our results. The average queueing time between the FEES request and examination was 8.9 days. The severe outlier with a queueing time of 252 days was excluded for being unrelated to the phenomenon studied. Queueing time can be reduced by minimizing the number of FEES requests without infrastructure or resource modifications, thereby avoiding increased costs. To this end, we investigated the potential of generating automatic classification models capable of predicting the severity of each case of OD based exclusively on the clinical examination and history.

The classification models analyzed yielded an accuracy rate of 66.4%, but with a high percentage of FN. We aimed to prevent FN, as they represent critically ill patients who should undergo FEES. The final classification model generated reduced the number of FN by 76.9%, despite having a low accuracy rate (47.6%). This method can reduce the number of patients undergoing FEES from 143 to 117 (82%), significantly shortening the queueing time. Although we used a set of parameters already recognized in the literature to construct the database, the accuracy rate of predicting the FOIS level was lower than expected. This may be attributed to the small sample size, the limitations of the classification algorithms in distinguishing between FOIS levels, and the inadequacy of the explanatory variables used.

Equation 1
Relationship between the queueing time before and after using the classifier

$$T = 8{,}9V \times \frac{p^{-1} - 1}{p^{-1} - V}$$

T = Average queueing time
p = Physician occupancy rate
V = Percentage of patients with indication for FEES

Figure 3
Schematic representation of the OD approach with and without using the classifier

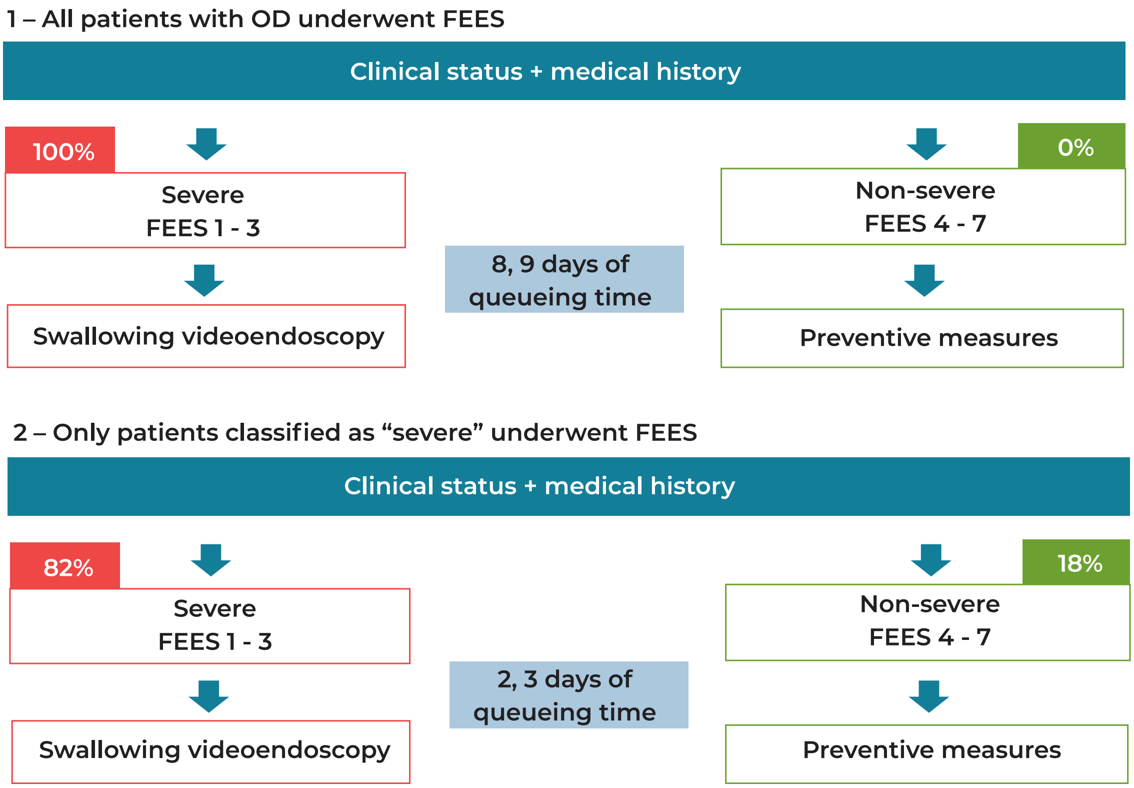


Diagram 1 describes the current situation, i.e., 100% of patients with suspected OD undergo FEES. This volume of requests results in an average queueing time of 8.9 days. Diagram 2 illustrates the reduced queueing time for FEES when the proposed classifier is used. In this case, 82% of patients would be selected to undergo FEES, which corresponds to an average queueing time of 2.3 days (a reduction of 74.2%). FEES, Fiber-optic endoscopic evaluation of swallowing; OD, oropharyngeal dysphagia.

In the current situation, with all patients undergoing FEES, the average response time between the FEES request and examination is 8.9 days. This time is significantly related to the occupancy rate of the physician conducting FEES, as the number of requests exponentially increases the queueing time. If the requests are limited to patients with severe OD (82% of all patients), the average queueing time can be reduced to 2.3 days.

This procedure can improve the quality of the service provided to patients with dysphagia requiring FEES in two different ways: by increasing the accuracy of the classification model in detecting patients with severe OD requiring FEES, and by significantly reducing the queueing time due to the reduced number of requested tests. This study has some limitations. A larger sample is required for more robust outcomes, particularly regarding the accuracy of the classifier that predicts the FOIS level. Additionally, it was a single-center study that exclusively evaluated patients hospitalized at the Centro Hospitalar Universitário Santo António, which may have resulted in bias. Regarding the data processing methods, particularly machine learning algorithms and analytical queueing models, the inherent hypotheses and their respective parameters were assumed, which may not be verified.

The results of this study appear promising and have the potential to stimulate scientific debate on the investigated topic. This study could serve as a foundation for developing a questionnaire designed to feed a classification model to predict the FOIS level without the need for additional diagnostic methods. Implementing this approach can reduce costs, queueing time, and the number of patients undergoing FEES without meeting the severity criteria.

Conclusion

The factors that most effectively explain the variations in FOIS levels are a history of RT, structural disorders, and surgery, collectively accounting for 17.3% of the variability.

Despite the small sample size, machine learning methods were used to generate a practically applicable classification model to differentiate between severe and non-severe cases of OD and reduce the FEES requests by 18%. This reduction in requests may decrease the queueing time by 74.2%, from 8.9 to 2.3 days. This approach can improve all service dimensions by enhancing patient comfort, reducing the number of FEES requests, and lowering the associated costs.

To date, this appears to be the first study aimed at improved patient comfort and preventing service overload through the early identification of severe OD cases.

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Conflict of Interests

The authors declare that they have no conflict of interest regarding this article.

Data Confidentiality

The authors declare that they followed the protocols of their work in publishing patient data.

Human and animal protection

The authors declare that the procedures followed are in accordance with the regulations established by the directors of the Commission for Clinical Research and Ethics and in accordance with the Declaration of Helsinki of the World Medical Association.

Privacy policy, informed consent and Ethics committee authorization

All the processed data were based in published reports that fulfilled privacy policy and ethical considerations.

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Scientific data availability

There are no publicly available datasets related to this work.

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