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Original Article

Integration Model of Clinical Variables and Computational Swallowing Biosignals in Neurogenic Oropharyngeal Dysphagia

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ABSTRACT

Clinical variables and biosignals can potentially be identified during the assessment, screening, and diagnostic characterization of neurogenic oropharyngeal dysphagia (NOD). This study aimed to develop an integration model to distinguish healthy individuals from patients with NOD by combining clinical variables with features extracted from surface electromyography (sEMG), laryngeal accelerometry (LA), and voice signals. These signals were recorded before and after swallowing different consistencies and volumes of food. A case-control study was conducted, including 80 healthy individuals and 86 patients diagnosed with NOD, and 158 clinical variables and 5,080 non-invasive swallowing-related signal features were collected. After dimensionality reduction, the data were integrated using logistic regression models. Statistically significant differences were found in 88 clinical variables, 36 latent variables from sEMG, 72 combined features from sEMG and LA, and 61 from voice signals. The final model included five clinical and four biosignal variables: two background variables, three findings from the physical examination, one sEMG feature from the infrahyoid region during water swallowing, one LA feature in the mediolateral axis during yogurt swallowing, and two voice subfeatures reflecting changes observed during continuous articulation and sustained phonation of the vowel "a." Together, these variables explained 90.6% of the variance in classifying individuals as NOD patients. The integration of computational swallowing methodologies using non-invasive signal processing with clinical variables may enhance screening and supplement gold-standard diagnostic tools in oropharyngeal dysphagia.

Keywords:
Swallowing; Swallowing disorders; Nervous System Diseases; Neuromuscular Diseases; Computer-Assisted Signal Processing

Modelo de integración entre variables clínicas y bioseñales de deglución computacional en disfagia orofaríngea neurogénica

RESUMEN

En la disfagia orofaríngea neurogénica (DON) existen variables clínicas y bioseñales potencialmente identificables durante su evaluación, tamizaje y caracterización diagnóstica. Este estudio desarrolló un modelo para diferenciar personas sanas de pacientes con DON mediante la integración de variables clínicas con características extraídas de señales de electromiografía de superficie (sEMG), acelerometría laríngea (AC) y voz, registradas antes y después de la deglución de distintas consistencias y volúmenes. Se diseñó un estudio de casos y controles que incluyó 80 personas sanas y 86 con diagnóstico de DON. Se recolectaron 158 variables clínicas y 5.080 variables derivadas de señales no invasivas asociadas a la deglución. Tras una reducción de variables, los datos fueron integrados mediante modelos de regresión logística. Se identificaron 88 variables clínicas con diferencias estadísticamente significativas, junto con 36 variables latentes de sEMG, 72 combinadas de sEMG y AC laríngea, y 61 de señales de voz. El modelo final integró cinco variables clínicas y cuatro características de las bioseñales: dos antecedentes, tres hallazgos al examen físico, una característica de sEMG en la región infrahioidea al deglutir agua, una característica de AC laríngea en el eje medio-lateral al deglutir yogur, y dos cambios en subcaracterísticas de la voz observados en articulación continua y en la fonación de la vocal "a". Estas variables explican el 90,6% del fenómeno de ser paciente con DON. La integración de metodologías de deglución computacional con variables clínicas podría mejorar el tamizaje y complementar las pruebas de referencia en disfagia orofaríngea.

Palabras clave:
Deglución; Trastornos de Deglución; Enfermedades del Sistema Nervioso; Enfermedades Neuromusculares; Procesamiento de Señales Asistido por Computador

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INTRODUCTION

Dysphagia is a swallowing disorder (Sejdic et al., 2019) that results from dysfunction in one or more of the phases of the swallowing mechanism—namely, the anticipatory (pre-oral) phase, oral preparatory phase, oral propulsive phase, pharyngeal phase, and esophageal phase. This disorder compromises both the safety and efficiency of swallowing, as well as the person's nutritional and respiratory status and overall quality of life (McCarty & Chao, 2021). Clinically, dysphagia is classified into oropharyngeal dysphagia (difficulty initiating swallowing) and esophageal dysphagia (sensation of food stuck in the esophagus) (Hurtte et al., 2023). Etiologically, we can find structural, motor, and functional causes (Suárez-Escudero et al., 2022). Structural causes involve conditions that narrow the oral, pharyngeal, or esophageal lumen; motor causes disrupt peristalsis and relaxation of the esophageal sphincter; and functional causes refer to impairments in the physiological processes of swallowing, including neurological control and neuromuscular coordination (Suárez-Escudero et al., 2022).

Although dysphagia may be a symptom of a systemic disease, its most common etiology is neurological (Altman et al., 2013). One of the most prevalent forms is neurogenic oropharyngeal dysphagia (NOD) (Suárez-Escudero et al., 2022), a functional disorder frequently associated with pulmonary and nutritional complications (Gallegos et al., 2017). Oropharyngeal dysphagia has been reported in 30% to 82% of patients with neurological and neurodegenerative diseases (Terré-Boliart et al., 2004), and its severity can range from mild to severe (Ciucci et al., 2019).

Dysphagia is a heterogeneous and complex multi-etiological syndrome with diverse phenotypic patterns depending on the underlying neurological disease (Warnecke et al., 2021), which is especially true in the case of NOD. It is commonly associated with a range of symptoms and signs that can be identified through formal screening and diagnostic tools, such as the Eating Assessment Tool-10 (EAT-10) (Zhang et al., 2023) and Clinical Swallowing Evaluation (CSE) (Cook, 2008; O'Horo et al., 2015). These tools allow for the clinical classification of dysphagia (oropharyngeal vs. esophageal) and aid in identifying potential etiologies. However, they fail to accurately and precisely characterize the presence or absence of specific subtypes, such as NOD.

In addition to clinical characteristics, such as symptoms and signs identified through medical history and physical examination, patients with NOD generate biosignals that can be recorded and analyzed using sensors during the swallowing of different volumes and consistencies. These biosignals hold significant clinical potential and can be captured using various technologies. Surface electromyography (sEMG) is a widely used method in which several electrodes are placed on the neck region to assess muscle activity during swallowing in both healthy individuals and those with dysphagia. Several studies have validated this technique (Hsu et al., 2013; Koyama et al., 2021; Vaiman et al., 2009). Another relevant technology is laryngeal accelerometry, which tracks the movement of the hyoid and detects dysphagia through sensors placed externally (Mao et al., 2019; Zoratto et al., 2010).

Additionally, voice quality analysis has been employed to assess changes associated with dysphagia (Waito et al., 2011). Phonetic test batteries, including assessments of lip, tongue, and jaw diadochokinesis, help predict dysphagia and detect aspiration in patients in intensive care units (Festic et al., 2016). These biosignals enable clinicians to examine both the electrophysiological and mechanical aspects of swallowing. However, to date, these techniques have been primarily used in isolation, following unimodal approaches. Integrating these tools under multimodal frameworks could significantly improve the detection and characterization of dysphagia, including NOD, by combining multiple sources of information to provide a more precise and comprehensive assessment (Roldan-Vasco, Orozco-Duque, et al., 2023).

The aforementioned underscores the need to develop new approaches to improve screening and diagnostic characterization processes. In recent years, advances have been made in signal and image processing algorithms, which are now used as methods for studying swallowing and supporting the diagnostic process. This approach, known as computational deglutition, has emerged as a translational subfield at the intersection of medicine, engineering, and signal/image processing (Sejdic et al., 2019).

Recent studies have explored the combination of biosignals in swallowing analysis. Examples include the integration of submental mechanomyography, nasal airflow, and biaxial cervical accelerometry (Lee et al., 2009); electromyography and bioimpedance (Schultheiss et al., 2014); and videofluoroscopy combined with high-resolution cervical auscultation (Donohue et al., 2021). Another study using multimodal analysis—combining sEMG signals from suprahyoid and infrahyoid regions with cervical auscultation based on triaxial accelerometry—showed that this integration improves the performance of automated classification models for dysphagia detection (Roldan-Vasco, Restrepo-Uribe, et al., 2023). Other research has combined sets of clinical variables to predict acute dysphagia

following radiotherapy (De Ruyck et al., 2013) and aspiration in oropharyngeal dysphagia (Heijnen et al., 2020). Moreover, a recent study proposed a model based solely on clinical variables—accessible through patient history and swallowing examination—that partially explains the presence of NOD (Escudero et al., 2024).

It is, therefore, plausible to consider that integrating clinical variables extracted from multiple groups of biosignals could help explain, identify, and classify patients with NOD. Combining these data may lead to models that support and complement the screening and diagnostic processes carried out by healthcare professionals. However, to date, no studies have integrated biosignals derived from computational deglutition analysis with clinical variables observed in patients with NOD.

This study aimed to develop an algorithm-based explanatory model capable of distinguishing between healthy individuals and patients with NOD by integrating clinical variables with features extracted from sEMG signals, laryngeal accelerometry, and voice quality before and after swallowing various volumes and consistencies.

METHOD

A case-control study was conducted using data from clinical assessments and non-invasive swallowing signals. The control group consisted of people without dysphagia or any neurological or neuromuscular comorbidities. In contrast, the case group was composed of patients diagnosed with neurogenic oropharyngeal dysphagia (NOD).

Participants

Sample size estimation was performed using Epidat®, yielding a total of 76 participants in the case group and 76 in the control group. The calculation was based on a sensitivity of 80%, as reported in the literature for the Clinical Swallowing Evaluation (CSE) (Cook, 2008), with a statistical power of 80% and a 95% confidence level. It was projected that the new clinical algorithm would increase sensitivity by 15% (expected sensitivity of 95%) compared to the CSE alone, while maintaining 80% power and a 95% confidence level.

Participants in the case group were recruited from 12 private speech-language therapy practices specializing in swallowing disorders, 10 healthcare institutions (IPS) offering dysphagia services, four long-term care facilities for older adults, and three patient foundations located in the Valle de Aburrá and San Nicolás regions of Antioquia, Colombia.

Participants without dysphagia (control group) were recruited from two senior community centers, two universities, and one neighborhood community board (*Junta de Acción Comunal*) located in the Valle de Aburrá (Medellín), as well as from healthy relatives of patients. Table 1 details the eligibility criteria for cases and controls.

A neurologist with clinical expertise in NOD assessed the eligibility of the case group, supported by a speech-language therapist trained in swallowing and dysphagia. On the other hand, a physician specialized in neurological rehabilitation with training in swallowing and dysphagia determined eligibility for the control group. The study was conducted from the first semester of 2019 to the first semester of 2022.

The research team assessed 288 individuals between March 2019 and December 2021, comprising 103 (35.7%) healthy controls and 185 (64.3%) with oropharyngeal dysphagia. The final sample consisted of 166 participants: 80 controls and 86 NOD cases (see Figure 1), all of whom underwent the CSE and three non-invasive biosignal protocols.

Among the NOD cases, 59.3% (51/86) were male, whereas 53.8% (43/80) of the controls were female. The median age in both groups was 61 years. In the case group, the etiology was primarily central neurological causes (88.4%, 76/86), followed by neuromuscular causes (11.6%, 10/86).

Table 1. Eligibility criteria for cases and controls.

Eligibility Criteria	Controls	Cases
Inclusion Criteria	Age ≥18, both sexes; no dysphagia or central, peripherical, or neuromuscular neurological diseases. Total score in the Eating Assessment Tool <3 Points. No comorbidities like head and neck cancer, COPD, or surgical procedures in the 2/3 lower part of the face or neck, no use of botulinum toxin.	Age ≥18, both sexes; presence of neurogenic oropharyngeal dysphagia of at least one month in duration. Diagnosis of central neurological or neuromuscular pathologies that, in their progress, have resulted in oropharyngeal dysphagia. Total score in the Eating Assessment Tool ≥3 points (Giraldo-Cadavid et al., 2016). Symptoms like coughing, a sensation of food being stuck in the throat, a choking sensation related to swallowing food, and/or voice changes when swallowing, as well as difficulty initiating swallowing or the need for multiple swallows to ingest food, as observed during physical examination.
Exclusion Criteria	Undergoing active endodontic procedures; presence of congenital malformations in the oral cavity, tongue, and neck; diagnosis of Sjögren's disease and cognitive impairment.	Exclusively esophageal dysphagia, mechanical, propulsion-related, or iatrogenic dysphagia; irradiated skin in the facial and/or cervical region; edema or hematoma in the orofacial and cervical area that prevents sensor placement; recent surgical dissection (<3 months) on the neck skin; severe hypoxemia (ambient oxygen saturation <80% unresponsive to oxygen therapy); deep brain stimulation implants; advanced-stage dementia that prevents understanding of simple commands for chewing and swallowing; presence of congenital structural malformations in the oral cavity, tongue, or neck; diagnosis of Sjögren's disease; and undergoing active endodontic procedures.

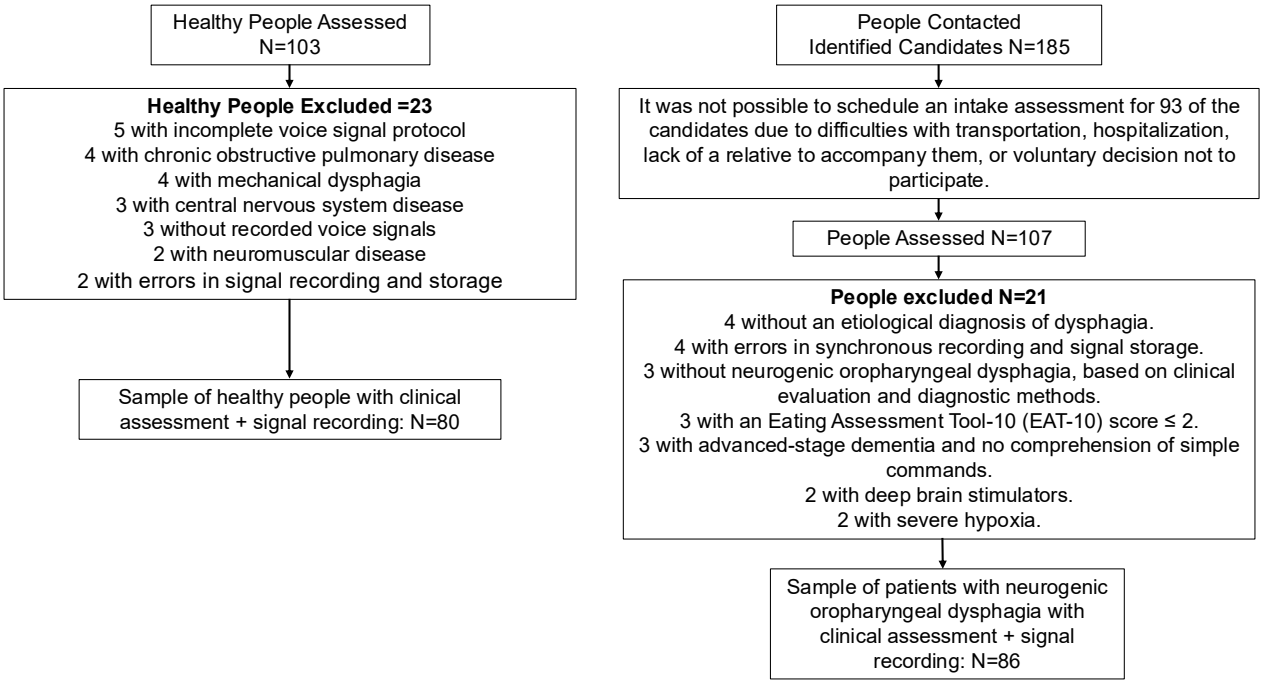

Figure 1. Flowchart of the recruitment and selection process for cases and controls.

Description of Instruments and Procedures

Both groups were assessed using a standardized protocol to ensure data comparability. The Eating Assessment Tool (EAT-10) was used to detect dysphagia. Additionally, a CSE protocol was implemented to collect clinical variables that could be integrated with features extracted from non-invasive swallowing signals to create an explanatory model for NOD. The signals were subsequently recorded to identify biomarkers to characterize and analyze the swallowing function and incorporate them into the model.

Eating Assessment Tool (EAT-10): This instrument was used for sample selection. It was chosen due to its validation in Colombia and its strong balance between sensitivity and specificity (Giraldo-Cadavid et al., 2016). A cutoff score of ≥3 points was considered to indicate the presence of dysphagia.

CSE: This protocol includes a medical history focused on swallowing characteristics and dysphagia symptoms. Additionally, information was gathered on medications that could affect swallowing (e.g., neuroleptics, barbiturates, anxiolytics, non-steroidal anti-inflammatory drugs, muscle relaxants, anticholinergics, and tricyclic antidepressants). A physical examination was conducted to assess the oral cavity, respiratory system, lower cranial nerves (including the trigeminal and facial nerves), orofacial movement, and pulmonary auscultation. Furthermore, an evaluation of the anatomy, function, sensitivity, and reflexes of the swallowing mechanism was performed, with an emphasis on the oral and pharyngeal phases (Ricci Maccarini et al., 2007). Height, weight, and oxygen saturation were also recorded. Variables extracted from the CSE were grouped into the following categories: (1) sociodemographic characteristics and medical history, (2) swallowing characteristics, (3) dysphagia symptoms, and (4) findings from the physical examination.

Non-invasive Swallowing Signal Recording: This was performed after the CSE. Biosignals from surface electromyography (sEMG), cervical accelerometry (CA), and voice were collected and selected for their capacity to assess the electrophysiological, kinematic, and phonatory dimensions of swallowing, respectively.

Surface electromyography signals were chosen because they provide data on the electrophysiological aspects of swallowing by capturing neuromuscular activity from muscle groups involved in the oral and pharyngeal phases (e.g., lip, masseter, supra- and infrahyoid regions) (Roldan-Vasco, Orozco-Duque, et al., 2023; Roldan-Vasco, Restrepo-Uribe, et al., 2023).

It is noteworthy that our research team had previously validated these biosignals (Roldan-Vasco et al., 2018, 2021; Roldan-Vasco, Orozco-Duque, et al., 2023; Roldan-Vasco, Restrepo-Uribe, et al., 2023). This procedure aimed to obtain recordings of these signals both before and after swallowing in participants from both groups.

To this end, three non-invasive biosignal detection and recording protocols were used while participants performed swallowing tasks with different food consistencies at sub-therapeutic volumes. Sub-therapeutic volumes were used as a safety measure, particularly for patients with NOD.

The three protocols are presented below:

Protocol 1: Surface electromyography (sEMG) signals were recorded from four muscle groups using electrodes designed to capture signals synchronously. The muscle regions included (a) orbicularis oris, (b) bilateral masseter, (c) bilateral suprahyoid, and (d) bilateral infrahyoid (Figure 2a). The sEMG signals were acquired using a Noraxon Ultium™ electromyograph with disposable silver/silver chloride (Ag/AgCl) electrodes (20 mm diameter, integrated gel), a sampling rate of 2 kHz, and a band-pass filter with cutoff frequencies between 10 and 500 Hz.

Following the setup of Protocol 1, an oral motor test was performed using specific volumes and consistencies in the following sequence: 5 mL of yogurt, pause; 10 mL of yogurt, pause; 20 mL of yogurt, pause (thick milk-based yogurt without fruit pieces); 3 grams of plain salted cracker, pause; saliva swallow, pause (after evaluating the risk of adverse events prior to administering water); 5 mL of water, pause; 10 mL of water, pause; and finally, 20 mL of water.

This sequence was adapted from the protocol by Sampaio et al. (2014), with reduced volumes (from 50 mL to 35 mL) as a safety measure. Our research group had validated and used the adjusted protocol in prior studies (Escudero et al., 2024; Roldan-Vasco, Orozco-Duque, et al., 2023; Roldan-Vasco, Restrepo-Uribe, et al., 2023). They included different consistencies because the physiological process of swallowing varies between solid (e.g., crackers) and liquid substances (e.g., water, yogurt, and saliva) (Matsuo & Palmer, 2008). During the swallowing of each consistency and volume, the signals were recorded digitally through sEMG, CA, or both.

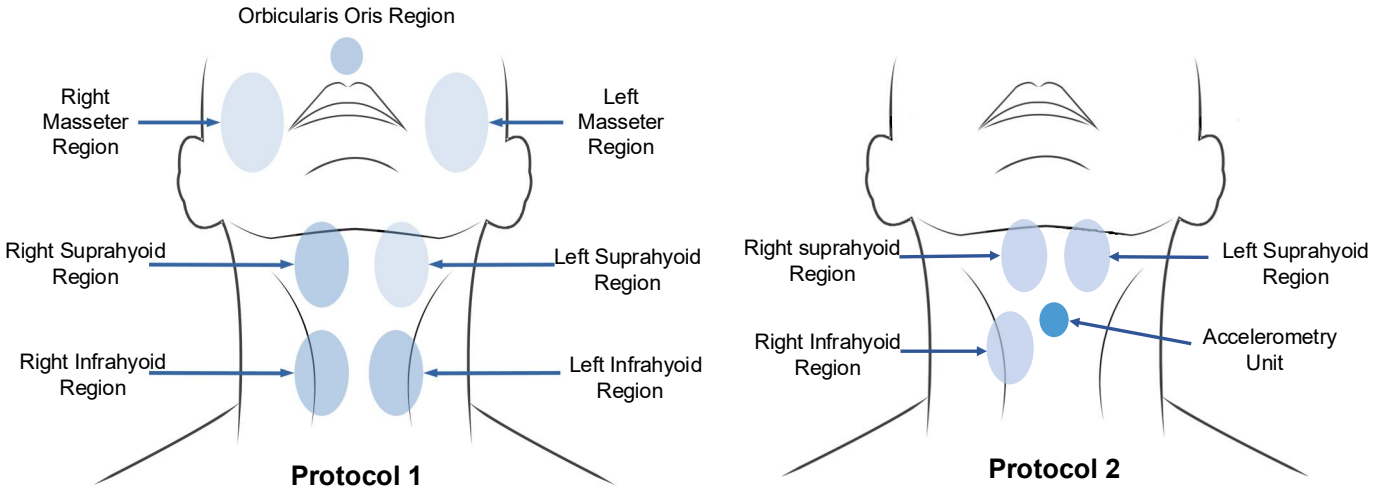

Figure 2. Electrode placement and positioning for protocols 1 and 2.
2a (Protocol 1): Electrodes were placed in four muscle regions: orbicularis oris, bilateral masseter, bilateral suprahyoid, and bilateral infrahyoid.
2b (Protocol 2): Electrodes were placed in the bilateral suprahyoid region and the right infrahyoid region, following the same anatomical references described for protocol 1. Additionally, a triaxial accelerometry unit was positioned in the anterior cervical region, on the skin overlying the larynx, using the space between the thyroid and cricoid cartilages as a reference.

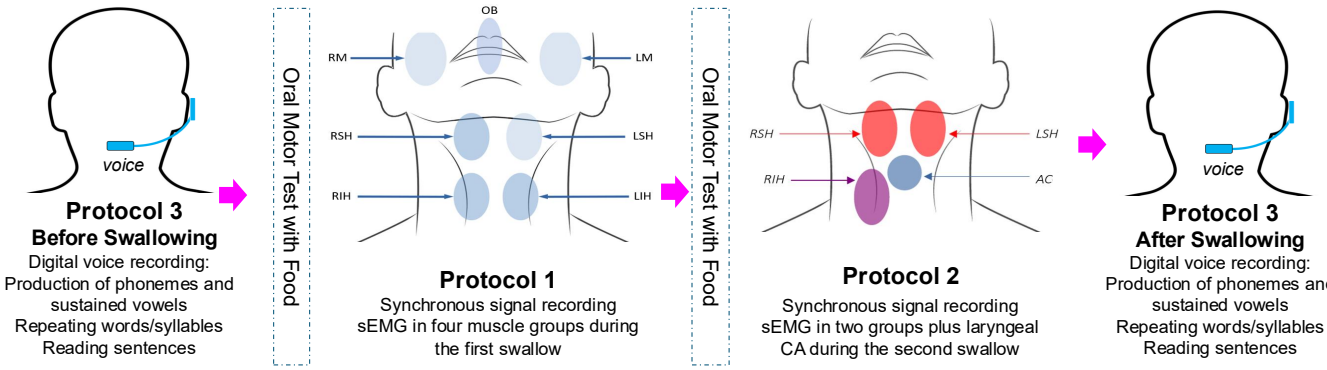

Figure 3. Sequence of the three protocols used to record the signals
OB: orbicularis oris region. RM: Right masseter region. LM: left masseter region. RSH: right suprahyoid region. LSH: left suprahyoid region. RIH: Right infrahyoid region. LIH: left infrahyoid region. AC: laryngeal accelerometry unit.

Protocol 2: This protocol involved recording sEMG signals from three of the four muscle groups analyzed in Protocol 1, aiming to detect neuromuscular activation (electrophysiological dimension). Simultaneously, a kinematic recording was performed using cervical accelerometry (CA) to capture displacements that occur during the pharyngeal phase of swallowing (mechanical dimension) (Roldan-Vasco, Restrepo-Uribe et al., 2023). Electrodes were positioned bilaterally over the suprahyoid region and on the right side of the infrahyoid region. Additionally, a triaxial analog accelerometer (MMA7362) was placed on the anterior cervical region, aligned with the larynx (Figure 2b).

The sEMG signal was obtained using the same equipment as in Protocol 1. The CA signal was captured using a triaxial analog accelerometer (MMA7362) designed to detect laryngeal movement. The accelerometer was connected to a NI-USB 6515 DAQ data acquisition board, which had a 10 kHz sampling rate and a band-pass filter with cutoff frequencies set at 0.1 kHz and 3 kHz. The three CA channels captured data along the anterior-

posterior (AP), superior-inferior (SI), and medial-lateral (ML) axes.

Once sensor placement for Protocol 2 was completed, we repeated the oral motor test described in Protocol 1.

Protocol 3: This consisted of digital voice recording using a Logitech H390 headset microphone and the Audacity software (Muse Group, 2021). Voice recordings were taken both before and after the oral motor test carried out in Protocols 1 and 2. Participants were asked to produce specific phonemes, words, and pre-designed sentences. Voice recordings help analyze speech-related dimensions (such as phonation, articulation, and prosody), given that swallowing and speech share common anatomical structures and neurological networks (Roldan-Vasco et al., 2021).

Figure 3 illustrates the protocol sequence and the position of the oral motor test within the signal recording process.

Data Processing

The sEMG and CA signal analysis began with noise removal using a method previously developed and reported by our research team (Sebastian et al., 2020). Subsequently, features in both time and frequency domains were extracted using a sliding window technique. This method generates a vector for each function and acquisition channel. The mean, standard deviation, skewness, kurtosis, and minimum and maximum values were then computed for each vector. This process aimed to scale each feature, resulting in a single data point per channel and feature. The sliding window size for both CA and sEMG signals was experimentally defined between 100 ms and 250 ms, with a 50% overlap between consecutive windows. Detailed signal processing procedures have been previously published (Roldan-Vasco, Restrepo-Uribe, et al., 2023).

For voice signals, preprocessing included data normalization using Sound eXchange (bitrate: 13 bps, downsampling: 8 kHz, band-pass filter between 0.2 kHz and 3.4 kHz). Subsequently, various speech-related features were extracted using Python and the Parselmouth library. The specifics of this processing are available in previously published work (Flórez-Gómez et al., 2022).

Data Analysis

Firstly, a descriptive analysis of the assessed variables was conducted, using the Shapiro–Wilk test to verify the normality of quantitative variables. Exploratory odds ratios (OR) were calculated with 95% confidence intervals. Then, a bivariate analysis was performed on clinical variables and the signals obtained from the three protocols.

Chi-square tests or Fisher's exact test were applied for qualitative variables. For quantitative signals, specific tests were selected based on data distribution; the Mann–Whitney U test was used for non-normally distributed variables. At the same time, Student's or Welch's *t*-tests were applied to normally distributed variables after testing for homogeneity with Levene's test (Protocols 1 and 2). Variables in Protocol 3 were analyzed using paired samples through the Wilcoxon test (for non-normal distributions) or Student *t*-test (for normal distributions). Variables with statistically significant differences ($p < 0.005$) were retained as a criterion for dimensionality reduction.

Significant variables were then subjected to Principal Component Analysis (PCA) as a data reduction method, with varimax rotation applied. The number of components was determined based on eigenvalues, supported by sphericity testing (Bartlett's test, $p < 0.001$), and sampling adequacy was evaluated using the Kaiser–Meyer–Olkin test (KMO ≥ 0.800 indicating good to excellent adequacy). Latent variables with correlations ≥ 0.8 within components were selected.

Binary logistic regression models were then constructed to classify cases (patients with NOD) and controls (healthy individuals). The parameters used for model construction included: a) Dependent variable: case/control status (reference category: healthy), b) Covariates: latent variables derived from signal data and qualitative clinical variables, c) Collinearity: assessed through the variance inflation factor (VIF), with ideal values between 1 and 3,

d) Model fit: evaluated using the Akaike Information Criterion (AIC), e) Model explanatory power: assessed via Nagelkerke's R^2 (R^2N), and f) OR estimation: reported with 95% confidence intervals.

Three independent models were developed, one for each protocol (sEMG, laryngeal CA, and voice), incorporating the clinical variables with statistically significant differences ($p < 0.005$) and the reduced latent variables from each protocol. Finally, the most relevant variables were integrated into a global model designed to discriminate between healthy individuals and those with NOD. Statistical analysis was performed using Jamovi® software, version 2.2 (The Jamovi Project, 2022).

The study was approved by the Health Research Ethics Committee of Universidad Pontificia Bolivariana (Act No. 7, June 1, 2017), the Ethics Committee of Fundación Hospitalaria San

Vicente Paúl (Act No. 35-2018, December 21, 2018), and the Ethics Committee of Clínica Somer (Act No. 01-2019, February 8, 2019). Written informed consent was obtained from all participants.

RESULTS

Four major sets of variables were obtained for both groups: 158 clinical variables derived from the CSE (25 sociodemographic and background characteristics, 38 swallowing features and dysphagia symptoms, 48 physical examination findings, and 47 clinical findings from the oral motor tests using different consistencies and volumes); 2,464 quantitative variables from Protocol 1 (eleven features extracted from sEMG signals across muscle groups, consistencies, and volumes); 1,491 quantitative variables from Protocol 2 (eight features from sEMG signals and two from CA); and 1,125 paired variables from Protocol 3 (five grouped vocal features subdivided into 19 sub characteristics, assessed before and after swallowing different consistencies and volumes).

When comparing cases and controls, 88 out of the 158 clinical variables (55.7%) showed statistically significant differences ($p < 0.005$) and were included in the construction of the logistic regression model (see Supplementary Table S1). Figure 4 summarizes the process of identifying, reducing, and distributing the clinical variables.

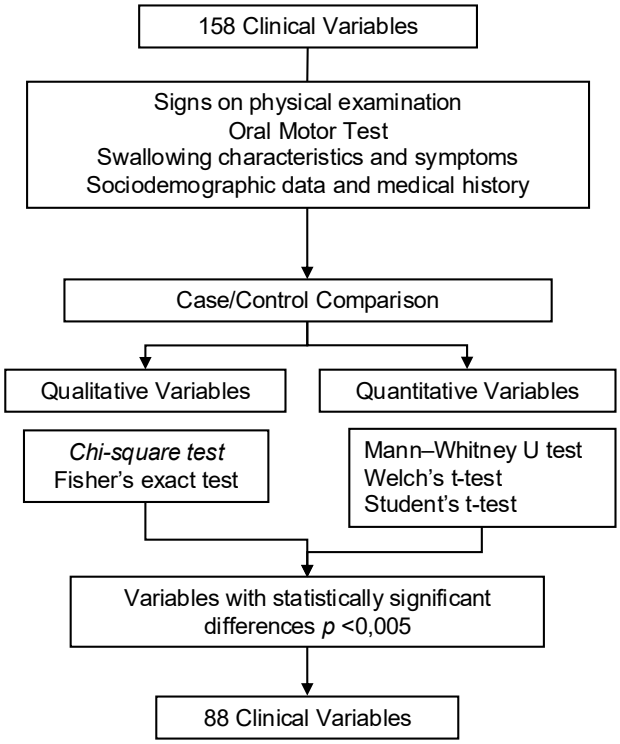

Figure 4. Number of clinical variables to differentiate people with neurogenic oropharyngeal dysphagia from healthy people.

In Protocol 1, 39.2% (966/2,464) of the quantitative variables exhibited statistically significant differences between groups ($p < 0.05$). Based on this outcome, 44 PCA models were developed and organized in blocks according to the extracted features and statistical properties. This dimensionality reduction process yielded 36 latent variables (from 966 significant variables) representative of the main sEMG signal dimensions. The latent sEMG variables from Protocol 1, along with their characterization, are provided in Supplementary Table S2.

In Protocol 2, 53.9% (804/1,491) of the quantitative variables showed significant differences between cases and controls. To reduce this set, 39 PCA models were implemented, structured by extracted features, statistical parameters, and sensor type (sEMG or laryngeal CA). This procedure reduced the 804 significant variables to 143 latent variables: 50.3% (72/143) derived from CA signals and 49.7% (71/143) from sEMG signals. The latent variables for laryngeal CA and sEMG from Protocol 2, along with their characterization, are detailed in Supplementary Tables S3 and S4.

In Protocol 3, 12.1% (136/1,125) of the paired variables showed statistically significant differences before and after swallowing in both groups. To reduce this set, 17 PCA models were performed, organized into blocks based on the five main vocal features—phonation, connected speech, sustained vowel, diadochokinesis, and prosody, along with their respective sub-characteristics. This process reduced the 136 significant paired variables to 61 latent variables, distributed as follows: phonation, 39.3% (24/61); connected speech, 37.7% (23/61); and sustained vowel, 23% (14/61). The latent voice variables derived from Protocol 3, along with their characterization, are detailed in Supplementary Table S5.

Figure 5 summarizes the comparison, identification, and dimensionality reduction process for the set of quantitative variables obtained from the three non-invasive biosignal acquisition protocols used in this study.

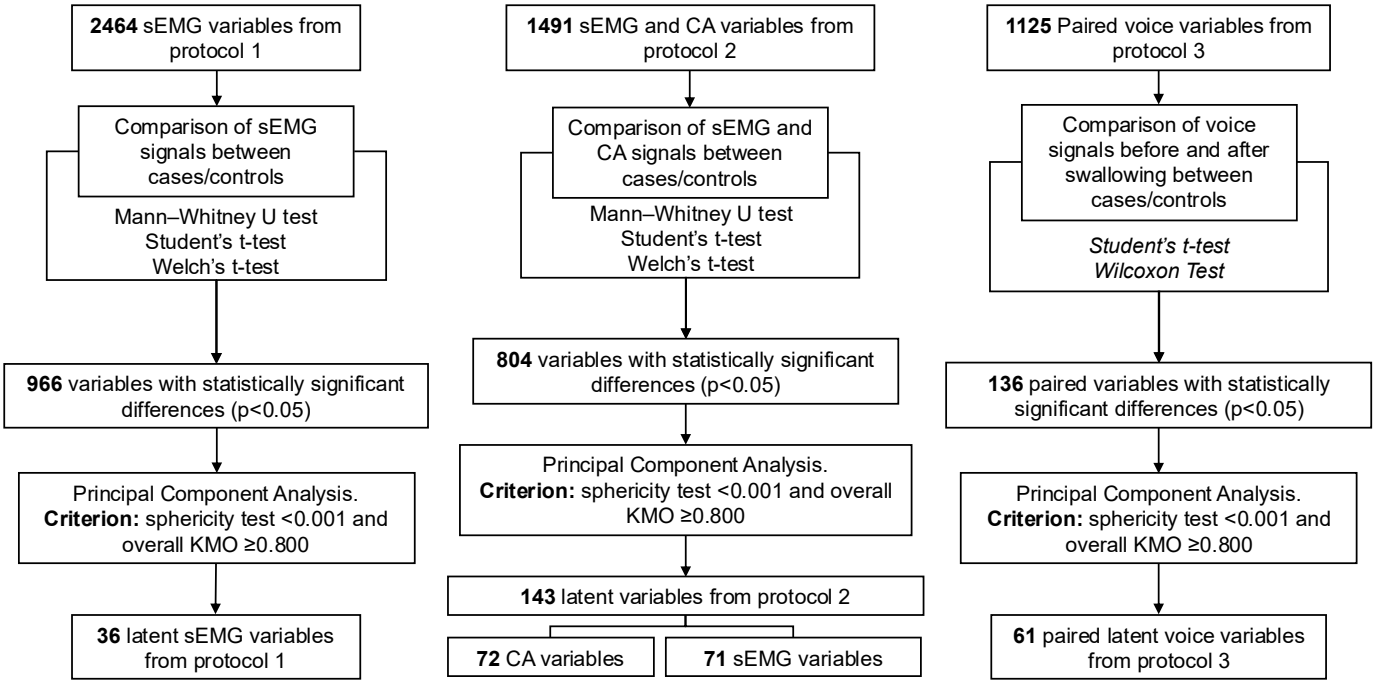

Figure 5. Summary of variable reduction from three protocols for electromyography, laryngeal accelerometry, and voice signals among people with neurogenic oropharyngeal dysphagia and healthy subjects.
sEMG: surface electromyography. KMO: Kaiser-Meyer-Olkin test. CA: cervical accelerometry.

The 88 clinical variables identified through the comparison process (p-value < 0.005), together with the 36 latent variables from Protocol 1, 143 from Protocol 2, and 61 from Protocol 3 (all derived through PCA-based dimensionality reduction), were included in the initial construction phase of three independent binary logistic regression models. At this stage, clinical variables were integrated with the biosignal features of each protocol separately (Figure 6).

Subsequently, the clinical and biosignal variables from each protocol that were retained in the initial models were selected and incorporated into a final integrative model. This model included variables: five clinical (two related to respiratory history and three from the physical examination, including one variable from the oral motor test involving solid consistency—cracker) and four biosignal variables (two from voice—Protocol 3, one from laryngeal CA—Protocol 2, and one from sEMG—Protocol 1). The final model achieved an AIC of 51.7 and a Nagelkerke R^2 of 0.906, with no evidence of collinearity between the selected variables (Table 2).

The final algorithm shows that the following variables collectively explain 90.6% of the probability of NOD: respiratory comorbidity, intubation longer than one week, impaired lateral lip movement, multiple swallows when ingesting a cracker-type consistency, changes in BMI, a zero-crossings feature from the sEMG signal in the left infrahyoid region while swallowing 20 ml of water, a logarithmic detector feature in the mediolateral axis of the laryngeal CA signal during 10 ml yogurt swallowing, a Bark band energy feature in connected speech before swallowing, and a first derivative feature in the phonation of the vowel "A" after swallowing. This model successfully integrates clinical variables with non-invasive swallowing biosignals, achieving high explanatory capacity.

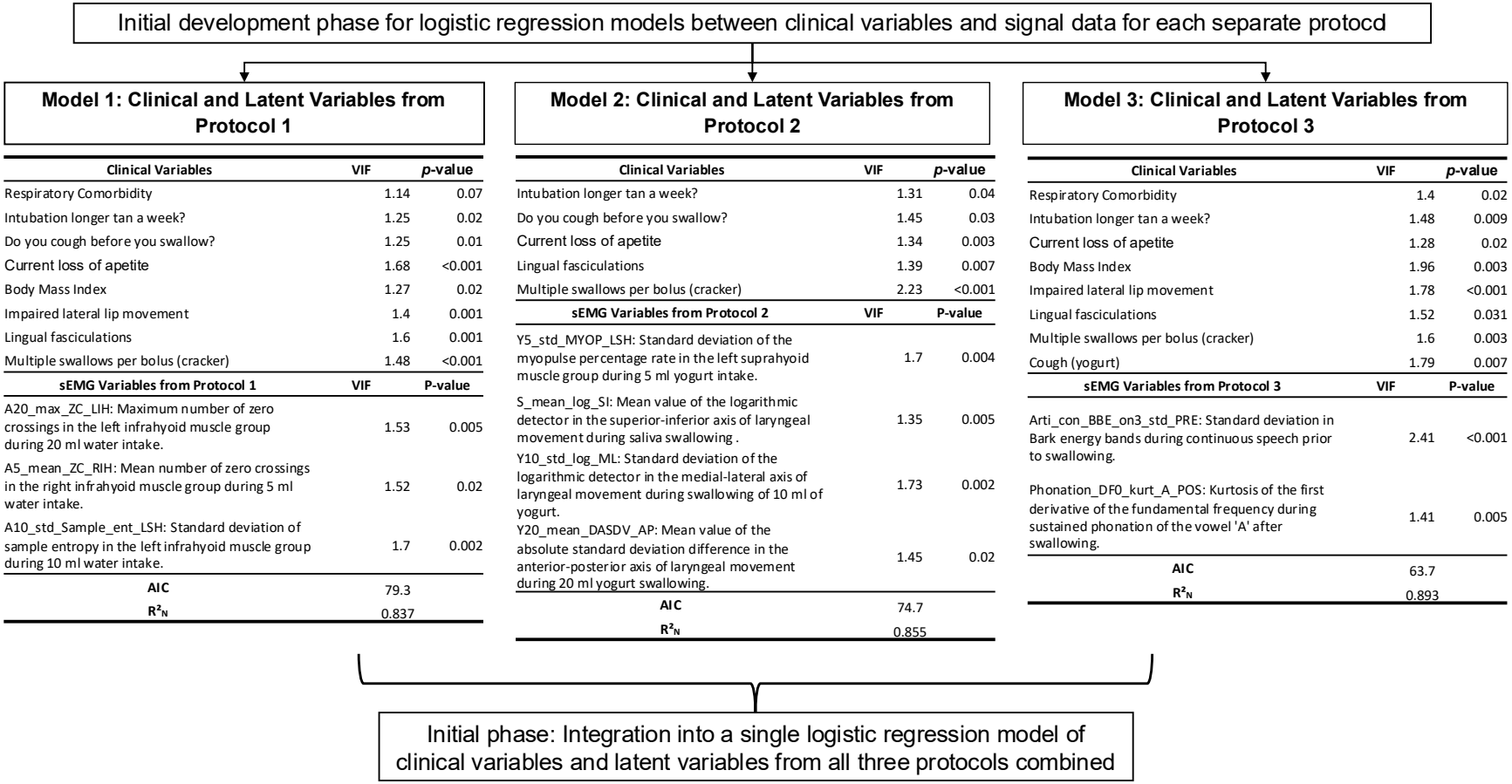

Figure 6. Summary of the initial development of three logistic regression models that included clinical variables and non-invasive swallowing signal variables to identify neurogenic oropharyngeal dysphagia. p: p-value. VIF: variance inflation factor. AIC: Akaike information criterion. R^2N: Nagelkerke's R^2.

Table 2. Final integrated model combining clinical variables with non-invasive swallowing signals to differentiate healthy individuals from patients with neurogenic oropharyngeal dysphagia.

Predictor	OR (CI 95%)	*p*-value	VIF
Respiratory Comorbidity	479.19 (2.29 –100075.74)	0.024	1.67
Intubation longer than a week	3353.64 (8.94 – 1.26 $^{e0+6}$)	0.007	1.89
Impaired lateral lip movement	57.96 (2.87 – 1168.94)	0.008	1.61
Multiple swallows when eating a cracker	27.74 (2.74 – 280.10)	0.005	1.37
Body Mass Index	0.75 (0.58 – 0.98)	0.038	1.95
p1_A20_max_ZC_LIH: Maximum number of zero crossings in the left infrahyoid muscle group during 20 ml water intake in protocol 1.	1.09 (1.01 – 1.18)	0.020	2.23
p2_Y10_std_log_ML: Standard deviation of the logarithmic detector in the medial-lateral axis of laryngeal movement during swallowing of 10 ml of yogurt in protocol 2.	1.55^{e-14} (1.42 $^{e-25}$ – 0)	0.014	1.67
p3_Arti_con_BBE_on3_std_PRE: Standard deviation in Bark energy bands during continuous speech prior to swallowing consistencies in protocol 3.	0 (2.64^{e0-5} – 0.06)	< .001	2.06
p3_Phonation_DF0_kurt_A_POS: Kurtosis of the first derivative of pitch during phonation of the vowel 'A' after swallowing consistencies in protocol 3	0.91 (0.86 – 0.96)	0.003	1.87
Model Fit Measures			
Model	**AIC**	**R^2_N**	
Clinical variables plus signals	51.7	0.906	

OR: odds ratio. CI 95: confidence interval at 95%. VIF: variance inflation factor. e: exponent. AIC: Akaike information criterion. R²N: Nagelkerke's R².

DISCUSSION

This study aimed to develop an algorithm capable of distinguishing individuals without dysphagia from patients with neurogenic oropharyngeal dysphagia (NOD). To achieve this, a multimodal model was built by integrating a wide range of clinical variables and features extracted from surface electromyography (sEMG), laryngeal accelerometry (CA), and voice quality, both before and after swallowing various food consistencies and volumes. The result was an original and pioneering model that, by combining five clinical variables and four biosignal features (obtained from sEMG across four muscle groups, laryngeal CA, and vocal characteristics), enables the distinction between individuals without dysphagia and those with NOD.

Model development was based on binary logistic regression incorporating both clinical and biosignal variables, and it required an extensive comparison and reduction process applied to a large number of clinical and biosignal features in both the case and control groups. This approach, novel in the multimodal analysis of swallowing, allowed for identifying variables capable of distinguishing healthy individuals from those with NOD. The features extracted from sEMG, CA, and voice were quantitative and derived through non-invasive methods during the swallowing of foods with varying textures and volumes, making this procedure a clear example of the advantages offered by computational deglutition (Sejdic et al., 2019).

Notably, clinical variables alone, as well as several individual features from sEMG, laryngeal CA, and voice (before and after swallowing), showed the capacity to differentiate patients with NOD from healthy controls. However, by applying dimensionality reduction techniques to identify the most relevant variables and subsequently integrating them through binary logistic regression models (combining clinical and biosignal variables), the overall classification and explanation of NOD were significantly enhanced. These results demonstrate the feasibility of developing models that combine clinical data and biosignals through multimodal analysis.

The final model indicates that the variables best predicting the presence of NOD (with an accuracy of 90.6%) include two medical history items obtained during anamnesis, three findings from physical examination, one sEMG signal feature in the infrahyoid region during water swallowing, one feature from the laryngeal CA signal in the mediolateral axis during yogurt swallowing, and two changes in subfeatures of the voice—specifically in continuous articulation and phonation of the vowel

"A." Interestingly, the final model did not include any direct symptoms of dysphagia, but was constructed based on the presence of comorbidities, clinical history, physical examination, and the objective quantification of three biosignals easily obtainable in a clinical setting. Therefore, this approach supports practical and straightforward implementation in professional practice.

It is noteworthy that, to date, no other studies have integrated sets of clinical and biosignal variables using binary logistic regression in dysphagia in general, nor in NOD specifically. In a previous study, Lee et al. (2009) used neural networks to analyze data from cervical accelerometry, mechanomyography, and nasal airflow to segment the swallowing process. However, their research did not include clinical variables, nor did it attempt to classify patients with or without NOD. Similarly, Chien and colleagues (Hsu et al., 2013) developed a system to assess dysphagia severity in 23 patients with myasthenia gravis by capturing swallowing sounds via a microphone and electromyography. Nonetheless, their study was limited to water swallowing, used sEMG electrodes only on the mentum and laryngeal regions, and did not integrate any clinical variables into the system.

Our research team had previously reported an explanatory clinical model based on binary logistic regression, developed by combining nine clinical variables and demonstrating an ability to predict the probability of NOD with 78.8% accuracy (Escudero et al., 2024). That model included the following variables: presence of respiratory comorbidity, intubation lasting more than one week, coughing before swallowing, current loss of appetite, changes in body mass index (BMI), impaired orofacial praxis (specifically lateral lip movement), presence of lingual fasciculations, need for multiple swallows when ingesting hard and dry consistencies, and coughing when swallowing thickened liquids. Five of these variables are shared with the current model: a history of respiratory comorbidity, prolonged intubation, impaired orofacial praxis, changes in body mass index (BMI), and multiple swallows for solid consistencies. Thus, by incorporating biosignals, the current model improved its explanatory capacity by 11.8%. This work highlights the importance of integrating non-invasive, routine instrumental variables with clinical data and developing new advances in understanding the complex phenomenon of dysphagia.

CONCLUSIONS

This study presents, for the first time, a model capable of predicting the presence of NOD with 90.6% accuracy by integrating five clinical variables and four biosignals. These findings demonstrate that the application of computational deglutition (Sejdic et al., 2019), utilizing non-invasive and quantitative approaches such as sEMG, laryngeal accelerometry, and voice analysis, is enhanced and complemented when combined with clinical variables routinely collected in healthcare practice. Furthermore, the results support the feasibility of implementing models, flowcharts, or algorithms that improve the classification and characterization of patients with NOD in clinical settings.

In the medium term, the aim is to develop additional explanatory models to distinguish between progressive and non-progressive neurogenic causes of dysphagia, as well as to assess the longitudinal behavior of biosignals and their predictive value for detecting improvement or deterioration in cases of functional oropharyngeal dysphagia.

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