

1 Characterizing effortful swallows from healthy community dwelling adults across the lifespan using high-resolution
2 cervical auscultation signals and MBSImP scores: A preliminary study

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44 **resolution cervical auscultation signals and MBSImP scores: A preliminary study**

45 **Abstract**

46 There is growing enthusiasm to develop inexpensive, noninvasive, portable methods that accurately assess
47 swallowing and provide biofeedback during dysphagia treatment. High-resolution cervical auscultation (HRCA),
48 which uses acoustic and vibratory signals from noninvasive sensors attached to the anterior laryngeal framework
49 during swallowing, is a novel method for quantifying swallowing physiology via advanced signal processing and
50 machine learning techniques. HRCA has demonstrated potential as a dysphagia screening method and diagnostic
51 adjunct to VFSSs by determining swallowing safety, annotating swallow kinematic events, and classifying swallows
52 between healthy participants and patients with a high degree of accuracy. However, its feasibility as a noninvasive
53 biofeedback system has not been explored. This study investigated 1. Whether HRCA can accurately differentiate
54 between non-effortful and effortful swallows; 2. Whether differences exist in Modified Barium Swallow Impairment
55 Profile (MBSImP) scores (#9, #11, #14) between non-effortful and effortful swallows. We hypothesized that HRCA
56 would accurately classify non-effortful and effortful swallows and that differences in MBSImP scores would exist
57 between the types of swallows. We analyzed 247 thin liquid 3mL command swallows (71 effortful) to minimize
58 variation from 36 healthy adults who underwent standardized VFSSs with concurrent HRCA. Results revealed
59 differences ($p < 0.05$) in 9 HRCA signal features between non-effortful and effortful swallows. Using HRCA signal
60 features as input, decision trees classified swallows with 76% accuracy, 76% sensitivity, and 77% specificity. There
61 were no differences in MBSImP component scores between non-effortful and effortful swallows. While preliminary
62 in nature, this study demonstrates the feasibility/promise of HRCA as a biofeedback method for dysphagia
63 treatment.

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65 **Key words:** dysphagia, videofluoroscopy, machine learning, cervical auscultation, biofeedback, treatment,
66 deglutition, deglutition disorders

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68 Introduction:

69 Within clinical settings, a common challenge for dysphagia practitioners remains the lack of inexpensive, portable,
70 and non-invasive dysphagia management methods available for assessment and treatment. To diagnose dysphagia,
71 instrumental methods remain the gold standard (e.g. videofluoroscopy [VF], fiberoptic endoscopic evaluation of
72 swallowing [FEES]). While these methods are objective and provide insight into swallowing physiology, there are
73 limitations to performing them including the cost, limited access in some settings (and countries), exposure to
74 radiation (i.e. VF), and inability for some patients to participate in the examination (e.g. patient size, COVID-19
75 restrictions, patient desire to forgo further imaging studies).

76 In addition to this, few accurate and non-invasive methods to provide biofeedback during dysphagia treatment are
77 readily available within clinical settings and few clinicians are trained in deploying these methods[1]. FEES and VF
78 have been implemented as biofeedback methods for dysphagia treatment and have been shown to be advantageous
79 for patient/caregiver education and developing individualized treatment plans[2–4]. In fact, clinician feedback and
80 participant/patient performance has been shown to be more accurate for certain swallowing maneuvers using VF
81 compared to other biofeedback methods (e.g. surface electromyography [sEMG])[3,4]. However, dysphagia
82 treatment using only VF for biofeedback is unrealistic within clinical settings due to the cost, radiation exposure,
83 and time constraints/accessibility[3,4]. Due to the limitations of FEES and VF as biofeedback methods for
84 treatment, other non-invasive modalities such as sEMG have been explored. Yet a study examining concurrent VF
85 and sEMG found very weak to moderate correlations between submental sEMG durations and temporal kinematic
86 measures of hyolaryngeal displacement using VF images when participants performed the Mendelsohn
87 maneuver[5]. A recent systematic review that examined biofeedback methods used in dysphagia treatment found
88 that accelerometry, sEMG, and tongue manometry were the most frequently used in research studies[6]. In three
89 studies, visual biofeedback using sEMG and accelerometry led to significantly improved hyoid bone displacement
90 (compared to a control) during dysphagia treatment that targeted functional swallowing exercises such as the
91 effortful swallow and Mendelsohn maneuver[6]. While these results are promising, study limitations included small
92 sample sizes, the heterogeneity of patients, and mixed evidence regarding whether biofeedback results in clinically
93 meaningful, functional changes in swallowing [5–9]. More specifically in studies using accelerometry, low quality
94 studies have been implemented with flawed study designs and the use of subjective and non-validated swallowing
95 outcome measures [6–9].

96 Due to the limitations of current biofeedback modalities, innovative methods for providing continuous monitoring
97 and biofeedback during dysphagia treatment are under investigation. One such modality is a novel wearable
98 electromyography sensor-array patch that has demonstrated similar signal quality as traditional, commercially
99 available sEMG during water swallow tasks[10]. Another potential biofeedback modality currently being explored is
100 high resolution cervical auscultation (HRCA)[11]. HRCA is a method of characterizing swallow function that
101 integrates information from acoustic and vibratory signals from non-invasive sensors (contact microphone, tri-axial
102 accelerometer) attached to the anterior laryngeal framework during swallowing. Following collection of HRCA
103 signals, HRCA signal features are extracted using advanced signal processing techniques to use the HRCA signal
104 features as input to machine learning algorithms to provide insight into swallowing physiology by using human
105 ratings of VF images as the “ground truth.” HRCA has demonstrated promise as a dysphagia screening method and
106 potential diagnostic adjunct to VF by classifying safe and unsafe swallows (as measured by the penetration-
107 aspiration scale)[11–17], tracking hyoid bone displacement in healthy adults and patients with suspected
108 dysphagia[18,19], annotating temporal swallow kinematic events in healthy adults and patients with suspected
109 dysphagia (e.g. durations of upper esophageal sphincter opening and laryngeal vestibule closure)[20–22],
110 categorizing swallows between healthy participants and different patient populations[23,24], and detecting clinical
111 ratings of swallow physiology in patients with suspected dysphagia using the Modified Barium Swallow Impairment
112 Profile (MBSImp)[25] with a high degree of accuracy[19,21]. However, the utility of HRCA’s capabilities to
113 noninvasively characterize these physiologic events, many of which are targets of behavioral augmentation via
114 compensatory swallowing maneuvers (e.g. effortful swallow, Mendelsohn maneuver), and differentiate between
115 swallows in which they are accurately deployed without imaging verification, has yet to be investigated. In our
116 clinical work, we have observed difficulty by patients in generalizing training in these maneuvers to accurate
117 performance when assessed using VF, likely due to the lack of ongoing performance evidence in the training stage
118 in which mass practice is deployed in clinic and home programs. Success of such an effort to provide ongoing,
119 noninvasive indications of accurate or inaccurate performance would be of value in demonstrating preliminary
120 efficacy of HRCA as a potential biofeedback method for dysphagia treatment.

121 Compensatory swallowing maneuvers (e.g. effortful swallow, Mendelsohn maneuver) are common dysphagia
122 rehabilitation techniques that are used to improve swallow function in patients with dysphagia by altering
123 swallowing physiology. The effortful swallow is one type of compensatory swallowing maneuver that is frequently

124 deployed in clinical settings for patients with dysphagia and has been explored in research studies in both healthy
125 adults and patients with dysphagia. Following dysphagia treatment targeting the effortful swallow, some patients
126 with dysphagia have exhibited decreased pharyngeal residue and decreased penetration/aspiration, but no changes in
127 upper esophageal sphincter (UES) opening diameter, duration of UES opening, laryngeal elevation, or hyoid
128 movement[26–29]. In healthy adults, the research evidence is mixed regarding the impact of effortful swallows on
129 swallowing physiology. For example, one study in healthy adults found that effortful swallows led to longer
130 durations for temporal swallow kinematic measurements (e.g. hyoid movement duration, duration of UES opening)
131 and increased pyriform sinus residue[30]. Other studies in healthy adults have found no differences in airway
132 protection or swallowing efficiency between non-effortful and effortful swallows[29]. While research studies have
133 examined differences in temporal kinematic measurements between non-effortful and effortful swallows in healthy
134 adults, no studies have examined differences between non-effortful and effortful swallows using a clinical rating
135 tool (e.g. MBSImP), few researchers have investigated noninvasive or non-imaging alternatives to VF that are
136 capable of determining whether the effortful swallow maneuver is accurately performed once a patient has been
137 properly trained. Such a system holds potential for enhancing clinician judgment of accurate performance (e.g.,
138 clinician feedback to patient) which is the source of accurate clinical cuing, and patient performance for effortful
139 swallows to mitigate maladaptive learning of the maneuver[3,4]. Therefore, this study investigated 1. Whether
140 HRCA can differentiate between non-effortful and effortful swallows performed by the same individuals; 2.
141 Whether there are differences in MBSImP components #9 (anterior hyoid excursion), #11 (laryngeal vestibular
142 closure), and #14 (pharyngoesophageal segment opening) between non-effortful and effortful swallows. We
143 hypothesized that HRCA combined with signal processing and machine learning algorithms would classify
144 swallows as non-effortful or effortful with a high degree of accuracy and that there would be differences in
145 MBSImP component scores #9, #11, and #14 between non-effortful and effortful swallows.

146 **Methods:**

147 Equipment and Procedures:

148 The Institutional Review Board for this institution approved this research study. All participants provided written
149 informed consent. Data analyses were performed on 247 thin liquid swallows from 36 healthy community dwelling
150 adults across the lifespan (19 male) between the ages of 49-86 (mean age 65.53 ± 7.67 years). This subset of data is
151 part of an ongoing prospective study that aims to analyze swallow function in healthy community dwelling adults

152 across the lifespan. Participants were enrolled in this research study based on the following inclusionary criteria
153 based on participant report: no history of swallowing difficulties, history of a neurological disorder, prior surgery to
154 the head or neck region, or chance of being pregnant (female participants). Participants underwent a standardized
155 videofluoroscopic swallow study (VFSS) procedure with concurrent HRCA and were imaged in the lateral plane.
156 For non-effortful swallows, participants swallowed ten thin liquid boluses in a randomized presentation order (five
157 3mL boluses via spoon, five self-selected “comfortable” cup sips). For the 3mL boluses via spoon, participants
158 were instructed to “Hold the liquid in your mouth and wait until I tell you to swallow it.” For the comfortable cup
159 sips, participants were instructed to “Take a comfortable sip of liquid and swallow it whenever you’re ready.” For
160 effortful swallows, participants swallowed one practice thin liquid water bolus and two 3mL thin liquid barium
161 boluses via spoon. During the practice effortful swallow, participants were instructed to “Swallow hard using all
162 your throat muscles.” For the effortful swallows that were recorded using VFSSs, participants were instructed to
163 “Hold the liquid in your mouth and wait until I tell you to swallow it” and then to “Swallow hard” during the exam.
164 For analyses purposes, only the 3mL thin liquid boluses via spoon were used to compare the non-effortful and
165 effortful swallows to minimize variation (e.g. bolus volume, utensil, command swallow). See Table 1 for the bolus
166 characteristics for swallows used for analyses for this study. The average fluoro time for participants was 1.06
167 minutes.

168 VFSS procedures were conducted using a standard fluoroscopy system (Precision 500D system, GE Healthcare,
169 LLC, Waukesha, WI) at a pulse rate of 30 pulses per second (PPS). A frame grabber module (AccuStream Express
170 HD, Foresight Imaging, Chelmsford, MA) captured the raw video signals at a rate of 73 frames per second (FPS).
171 Prior to analysis, the video files were down sampled to 30FPS. HRCA signals were collected concurrently during
172 the VFSSs via a tri-axial accelerometer (ADXL 327, Analog Devices, Norwood, Massachusetts) that was powered
173 by a 3V output (model 1504, BK Precision, Yorba Linda, California) and a contact microphone. The accelerometer
174 and contact microphone were placed in custom casings to ensure adequate contact for signal acquisition during data
175 collection. The noninvasive HRCA sensors were placed on the anterior laryngeal framework at the level of the
176 cricoid cartilage with tape after cleaning participants’ neck region with alcohol pads. The sensors were carefully
177 placed to avoid interfering with VFSS images, to ensure adequate signal acquisition, and to ascertain alignment of
178 the tri-axial accelerometer with the participant’s neck[11,31]. The precise placement of the accelerometer and
179 contact microphone can be viewed in Figure 1.

180 Signals from the accelerometer and the microphone were hardware-bandpass filtered from 0.1 to 3000 Hz (model
181 P55, Grass Technologies, Warwick, Rhode Island), amplified, and digitized using a data acquisition device
182 (National Instruments 6210 DAQ) at a sampling rate of 20kHz with the Signal Express program in LabView
183 (National Instruments, Austin, Texas). Before analysis, the signals were then down sampled to 4kHz to smooth out
184 high frequency noise.

185 Prior to data analysis for this study, one trained rater segmented video files into individual swallow segments with
186 ongoing intra-rater reliability within a 3-frame tolerance of 100% based on randomly re-coding one out of every ten
187 swallows. Another trained rater coded 10% of swallows for inter-rater reliability with intra-class coefficients (ICCs)
188 of at least 0.9 [32]. The methods for swallow segmentation have been described in previous publications [14,33]. No
189 other temporal kinematic measurements were performed aside from identifying the onset and offset of each
190 swallow, and the sole purpose of these measurements was to segment the video files into individual swallows.

191 MBSImP ratings:

192 An MBSImP certified clinician completed all MBSImP ratings for components #9, #11, and #14. Before performing
193 swallowing ratings, inter-rater reliability was established by completing the MBSImP reliability test with at least
194 80% exact agreement for all MBSImP component scores. Ongoing intra-rater reliability was maintained by
195 randomly selecting one swallow to re-code every ten swallows with 100% exact agreement. Inter-rater reliability
196 was conducted on 10% of swallows by another certified MBSImP clinician with 79% exact agreement for
197 components #9, #11, and #14.

198 Pre-Processing and feature extraction from HRCA signals:

199 An autoregressive model was used to build a digital finite impulse filter to remove the device noise associated with
200 each of the sensors. The filters were designed to remove the baseline noise present in the sensors' output when no
201 physical input is applied. Afterwards, motion artifacts and low frequency noise such as head movement, were
202 removed using fourth-order splines. Finally, wavelet denoising was used to eliminate any additional noise that might
203 exist in the signals[17,20,21]. The onset and offset of swallows were taken from the segmented videos after applying
204 the proper sampling mapping between videos and signals. The signals were then segmented using the mapped onset
205 and offset times for feature extraction[33]. A summary of the features extracted from the HRCA signals and the
206 explanations of their meanings can be viewed in Table 2. Nine features were extracted from the contact microphone
207 and the three directions of the tri-axial accelerometer (anterior-posterior, superior-inferior, medial-lateral) for a total

208 of 36 signal features. This set of features has been proven effective in differentiating between HRCA signals from
209 different types of swallows and extraction of multiple swallow kinematics[17,21,24,34].

210 Data Analysis:

211 We fit linear mixed models to examine the association between HRCA signal features, non-effortful swallows, and
212 effortful swallows. We used multiple supervised machine learning classifiers (e.g. support vector machines [SVM],
213 Naïve Bayes, decision trees, linear discriminant analysis) that use HRCA signal features as input to classify
214 swallows as non-effortful or effortful. The supervised machine learning classifiers were deployed using the entire set
215 of HRCA signal features (n=36), the features that were statistically significant (n=9), and the linearly independent
216 features (as determined by performing a principal component analysis [PCA]). A leave-one-out procedure was used
217 to evaluate the classification accuracy of all the used classifiers. A leave-one-out procedure involves training the
218 classifier on the entire data set except for one randomly selected swallow which is used to test the accuracy of the
219 classifier. This training and testing procedure were repeated until all swallows in the data set were tested at least
220 once. The accuracy, sensitivity, and specificity of all supervised machine learning classifiers was then calculated.
221 We fit linear mixed models to determine if there were differences in MBSImP component scores #9, #11, and #14
222 between the non-effortful and the effortful swallows. SPSS (IBM, Armonk, NY) was used to fit the linear mixed
223 models. MATLAB (The MathWorks, Inc., Natick, MA) and R (The R Foundation) were used to construct and
224 evaluate the performance of the supervised machine learning classifiers.

225 **Results:**

226 Results revealed that there was a statistically significant ($p < 0.05$) difference in 9 HRCA signal features between the
227 non-effortful and effortful swallows. Complete results from the linear mixed model can be viewed in Table 3. From
228 the microphone signals, statistically significant features included standard deviation, peak frequency, spectral
229 centroid, bandwidth, and wavelet entropy. From the anterior-posterior and medial-lateral accelerometer axes,
230 standard deviation was the only statistically significant feature. From the superior-inferior accelerometer axis,
231 statistically significant features included standard deviation and wavelet entropy. Figures 2 and 3 illustrate two
232 examples of the differences in signal features (e.g. standard deviation, peak frequency) between the non-effortful
233 and effortful swallows.

234 After evaluating the performance of all supervised machine learning classifiers using the entire set of HRCA signal
235 features (36), the features that were statistically significant (9), and the statistically independent features; decision

236 trees and linear discriminant analysis had the best performance. Using the 9 most significant HRCA signal features
237 as input, decision trees classified swallows as non-effortful or effortful with 76% accuracy, 76% sensitivity, and
238 77% specificity. A complete summary of the performance of the different supervised machine learning classifiers
239 can be viewed in Table 4. For MBSImP component scores, results from the linear mixed model revealed that there
240 were no significant differences ($p>0.05$) in MBSImP component scores #9, #11, and #14 between the non-effortful
241 and effortful swallows. Table 5 shows a complete summary of the MBSImP component scores for the non-effortful
242 and effortful swallows.

243 **Discussion:**

244 This study found that HRCA combined with advanced signal processing and machine learning techniques could
245 accurately and autonomously classify swallows from healthy adults as non-effortful or effortful without imaging.
246 This is of particular clinical interest given the results indicating that analysis of the VF data, which is commonly
247 used to confirm treatment effect in training of the effortful swallow, did not generate significant differences in the
248 MBSImP components measured. While preliminary in nature, these results provide evidence regarding the potential
249 of HRCA as a biofeedback method and an indicator of accurate performance for use by the clinician in providing
250 reinforcement to the patient, for dysphagia treatment protocols in the future. These results are especially
251 encouraging given that participants had minimal training (i.e. one practice swallow) prior to performing two
252 effortful swallows during the videofluoroscopic evaluation. Having an inexpensive, non-invasive, portable, easy-to-
253 use method for providing biofeedback during dysphagia treatment would significantly improve current dysphagia
254 management of patients by providing clinicians and patients with immediate insight into performance of swallowing
255 maneuvers and exercises such as the effortful swallow. These findings expand upon previous research studies that
256 have demonstrated the potential of HRCA as an effective dysphagia screening method and adjunct to VF when
257 instrumental swallow evaluations are not feasible and provide evidence to support pursuing HRCA as a biofeedback
258 method. Interestingly, in addition to these findings, we did not detect a statistically significant difference in
259 MBSImP component scores (#9, #11, #14) between non-effortful and effortful swallows. These results contribute to
260 the mixed evidence base examining differences between non-effortful and effortful swallows in healthy adults
261 [29,30]. It is also possible that MBSImP ratings may not be sensitive enough to detect subtle changes in swallowing
262 physiology because the MBSImP is a somewhat subjective, ordinal rating scale with a limited range of scores. This

263 may particularly be true in the present study because all participants were healthy community dwelling adults with
264 no report of swallowing difficulties; leading to a ceiling effect with MBSImP ratings.

265 Future studies should replicate this research work by examining HRCA's ability to classify non-effortful and
266 effortful swallows with a larger sample of swallows that includes swallows from both healthy adults and patients
267 with dysphagia. Including a larger and more variable sample of swallows will assist in improving the accuracy of the
268 supervised machine classifier and may also allow us to detect differences in MBSImP component scores between
269 non-effortful and effortful swallows. In addition to this, future studies should examine HRCA's ability to provide
270 real-time continuous biofeedback during a treatment session targeting effortful swallows. It will be important to
271 explore HRCA's ability to provide insight into performance of other swallowing maneuvers/exercises that would
272 benefit from biofeedback (e.g. Mendelsohn maneuver) as well.

273 **Limitations:**

274 The purpose of this research study was to determine the efficacy of HRCA as an inexpensive, noninvasive, portable
275 dysphagia biofeedback method. Because of the preliminary nature of this study, a relatively small sample of
276 swallows were included for analyses (n=247), which may have resulted in inadequate statistical power for
277 comparing MBSImP component scores between non-effortful and effortful swallows. In addition to this, only
278 swallows from healthy community dwelling adults across the lifespan were included in the analysis and only three
279 MBSImP component scores were examined. This likely limited the range of swallows included (e.g. finite range of
280 MBSImP component scores, limited severity range) and also limits the generalization of findings to patients with
281 dysphagia in clinical settings. Due to time constraints while collecting data in a University hospital, participants
282 received minimal training or practice prior to completing effortful swallows, which may have impacted their
283 performance. In addition to this, we did not confirm accurate performance of effortful swallows with a validated
284 measurement tool such as sEMG or manometry, so it is possible not all participants performed this compensatory
285 maneuver correctly. Data was collected using a strict, standardized VF protocol to minimize radiation exposure to
286 healthy community dwelling adults. As such, participants only swallowed thin liquid boluses and only two effortful
287 swallows were collected from each participant during the VF procedure. Future studies should examine HRCA's
288 ability to classify non-effortful and effortful swallows across various conditions (e.g. bolus volume, bolus viscosity,
289 utensil) and across more trials from each participant.

290 **Conclusion:**

291 This preliminary study found that HRCA signal features combined with decision trees and linear discriminant
292 analysis classified swallows as non-effortful or as an effortful swallow with up to 76% accuracy, 76% sensitivity,
293 and 77% specificity. These results provide promising evidence regarding the efficacy of using HRCA as a
294 monitoring system and biofeedback method for dysphagia treatment in the future. Future studies should expand
295 upon these findings to improve the machine learning algorithm performance and to further validate HRCA as a
296 biofeedback method by analyzing a larger number of swallows (e.g. patient and healthy community dwelling adults)
297 and by exploring the efficacy of using HRCA as a biofeedback method for other dysphagia treatment targets (e.g.
298 Mendelsohn maneuver). This inexpensive, noninvasive, portable method has the potential to transform dysphagia
299 rehabilitation by providing real-time feedback regarding treatment performance.

300 **Compliance with Ethical Standards:**

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305

306 Conflict of interest: We have no conflicts of interest to declare.

307

308 Ethical Approval: All procedures performed in studies involving human participants were in accordance with the
309 ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and
310 its later amendments or comparable ethical standards.

311

312 Informed Consent: Informed consent was obtained from all individual participants included in the study.

313

314 References

- 315 [1] M.A. Crary, M.E. Groher, Basic concepts of surface electromyographic biofeedback in the
316 treatment of dysphagia: A tutorial, *Am. J. Speech. Lang. Pathol.* 9 (2000) 116.
317 doi:10.1044/1058-0360.0902.116.
- 318 [2] S.B. Leder, S. Novella, H. Patwa, Use of fiberoptic endoscopic evaluation of swallowing
319 (FEES) in patients with amyotrophic lateral sclerosis., *Dysphagia.* 19 (2004) 177–181.
320 doi:10.1007/s00455-004-0009-2.
- 321 [3] A.M. Azola, K.L. Sunday, I.A. Humbert, Kinematic visual biofeedback improves accuracy
322 of learning a swallowing maneuver and accuracy of clinician cues during training.,
323 *Dysphagia.* 32 (2017) 115–122. doi:10.1007/s00455-016-9749-z.
- 324 [4] A.K. Vose, A. Marcus, I. Humbert, Kinematic Visual Biofeedback Improves Accuracy of
325 Swallowing Maneuver Training and Accuracy of Clinician Cues During Training in Stroke
326 Patients with Dysphagia., *PM R.* 11 (2019) 1159–1169. doi:10.1002/pmrj.12093.
- 327 [5] A.M. Azola, L.R. Greene, I. Taylor-Kamara, P. Macrae, C. Anderson, I.A. Humbert, The
328 Relationship Between Submental Surface Electromyography and Hyo-Laryngeal
329 Kinematic Measures of Mendelsohn Maneuver Duration., *J. Speech Lang. Hear. Res.* 58
330 (2015) 1627–1636. doi:10.1044/2015_JSLHR-S-14-0203.
- 331 [6] J.K. Benfield, L.F. Everton, P.M. Bath, T.J. England, Does Therapy With Biofeedback
332 Improve Swallowing in Adults With Dysphagia? A Systematic Review and Meta-
333 Analysis., *Arch. Phys. Med. Rehabil.* 100 (2019) 551–561.
334 doi:10.1016/j.apmr.2018.04.031.
- 335 [7] N.P. Reddy, D.L. Simcox, V. Gupta, G.E. Motta, J. Coppenger, A. Das, et al.,
336 Biofeedback therapy using accelerometry for treating dysphagic patients with poor
337 laryngeal elevation: case studies., *J Rehabil Res Dev.* 37 (2000) 361–372.
- 338 [8] C.-M. Li, T.-G. Wang, H.-Y. Lee, H.-P. Wang, S.-H. Hsieh, M. Chou, et al., Swallowing
339 Training Combined With Game-Based Biofeedback in Poststroke Dysphagia., *PM R.* 8
340 (2016) 773–779. doi:10.1016/j.pmrj.2016.01.003.
- 341 [9] C.-M. Li, H.-Y. Lee, S.-H. Hsieh, T.-G. Wang, H.-P. Wang, J.-J.J. Chen, Development of
342 innovative feedback device for swallowing therapy, *J. Med. Biol. Eng.* 36 (2016) 357–368.
343 doi:10.1007/s40846-016-0146-8.
- 344 [10] C. Kantarcigil, M.K. Kim, T. Chang, B.A. Craig, A. Smith, C.H. Lee, et al., Validation of
345 a novel wearable electromyography patch for monitoring submental muscle activity during
346 swallowing: A randomized crossover trial., *J. Speech Lang. Hear. Res.* 63 (2020) 3293–
347 3310. doi:10.1044/2020_JSLHR-20-00171.
- 348 [11] J.M. Dudik, J.L. Coyle, E. Sejdić, Dysphagia screening: Contributions of cervical
349 auscultation signals and modern signal-processing techniques., *IEEE Trans. Hum. Mach.*
350 *Syst.* 45 (2015) 465–477. doi:10.1109/THMS.2015.2408615.
- 351 [12] E. Sejdić, C.M. Steele, T. Chau, Classification of penetration--aspiration versus healthy
352 swallows using dual-axis swallowing accelerometry signals in dysphagic subjects., *IEEE*
353 *Trans. Biomed. Eng.* 60 (2013) 1859–1866. doi:10.1109/TBME.2013.2243730.
- 354 [13] J.M. Dudik, I. Jestrović, B. Luan, J.L. Coyle, E. Sejdić, A comparative analysis of
355 swallowing accelerometry and sounds during saliva swallows., *Biomed Eng Online.* 14
356 (2015) 3. doi:10.1186/1475-925X-14-3.
- 357 [14] J.M. Dudik, A. Kurosu, J.L. Coyle, E. Sejdić, A comparative analysis of DBSCAN, K-
358 means, and quadratic variation algorithms for automatic identification of swallows from
359 swallowing accelerometry signals., *Comput Biol Med.* 59 (2015) 10–18.
360 doi:10.1016/j.combiomed.2015.01.007.

- 361 [15] I. Jestrović, J.M. Dudik, B. Luan, J.L. Coyle, E. Sejdić, Baseline characteristics of cervical
 362 auscultation signals during various head maneuvers., *Comput Biol Med.* 43 (2013) 2014–
 363 2020. doi:10.1016/j.combiomed.2013.10.005.
- 364 [16] J.M. Dudik, J.L. Coyle, A. El-Jaroudi, Z.-H. Mao, M. Sun, E. Sejdić, Deep learning for
 365 classification of normal swallows in adults., *Neurocomputing.* 285 (2018) 1–9.
 366 doi:10.1016/j.neucom.2017.12.059.
- 367 [17] C. Yu, Y. Khalifa, E. Sejdic, Silent Aspiration Detection in High Resolution Cervical
 368 Auscultations, *IEEE EMBS International Conference on Biomedical & Health Informatics*
 369 (BHI), 2019.
- 370 [18] S. Mao, Z. Zhang, Y. Khalifa, C. Donohue, J.L. Coyle, E. Sejdic, Neck sensor-supported
 371 hyoid bone movement tracking during swallowing., *R. Soc. Open Sci.* 6 (2019) 181982.
 372 doi:10.1098/rsos.181982.
- 373 [19] C. Donohue, S. Mao, E. Sejdić, J.L. Coyle, Tracking hyoid bone displacement during
 374 swallowing without videofluoroscopy using machine learning of vibratory signals.,
 375 *Dysphagia.* (2020). doi:10.1007/s00455-020-10124-z.
- 376 [20] Y. Khalifa, C. Donohue, J.L. Coyle, E. Sejdic, Upper esophageal sphincter opening
 377 segmentation with convolutional recurrent neural networks in high resolution cervical
 378 auscultation, *IEEE J Biomed Health Inform.* 25 (2021) 493–503.
 379 doi:10.1109/JBHI.2020.3000057.
- 380 [21] C. Donohue, Y. Khalifa, S. Perera, E. Sejdić, J.L. Coyle, How closely do machine ratings
 381 of duration of UES opening during videofluoroscopy approximate clinician ratings using
 382 temporal kinematic analyses and the mbsimp?, *Dysphagia.* (2020). doi:10.1007/s00455-
 383 020-10191-2.
- 384 [22] S. Mao, A. Sabry, Y. Khalifa, J.L. Coyle, E. Sejdic, Estimation of laryngeal closure
 385 duration during swallowing without invasive X-rays., *Future Gener. Comput. Syst.* 115
 386 (2021) 610–618. doi:10.1016/j.future.2020.09.040.
- 387 [23] A. Kurosu, J.L. Coyle, J.M. Dudik, E. Sejdic, Detection of swallow kinematic events from
 388 acoustic high-resolution cervical auscultation signals in patients with stroke., *Arch. Phys.*
 389 *Med. Rehabil.* 100 (2019) 501–508. doi:10.1016/j.apmr.2018.05.038.
- 390 [24] C. Donohue, Y. Khalifa, S. Perera, E. Sejdić, J.L. Coyle, A preliminary investigation of
 391 whether HRCA signals can differentiate between swallows from healthy people and
 392 swallows from people with neurodegenerative diseases., *Dysphagia.* (2020).
 393 doi:10.1007/s00455-020-10177-0.
- 394 [25] B. Martin-Harris, M.B. Brodsky, Y. Michel, D.O. Castell, M. Schleicher, J. Sandidge, et
 395 al., MBS measurement tool for swallow impairment--MBSImp: establishing a standard.,
 396 *Dysphagia.* 23 (2008) 392–405. doi:10.1007/s00455-008-9185-9.
- 397 [26] M. Bülow, R. Olsson, O. Ekberg, Videomanometric analysis of supraglottic swallow,
 398 effortful swallow, and chin tuck in patients with pharyngeal dysfunction., *Dysphagia.* 16
 399 (2001) 190–195. doi:10.1007/s00455-001-0065-9.
- 400 [27] M. Bülow, R. Olsson, O. Ekberg, Supraglottic swallow, effortful swallow, and chin tuck
 401 did not alter hypopharyngeal intrabolus pressure in patients with pharyngeal dysfunction.,
 402 *Dysphagia.* 17 (2002) 197–201. doi:10.1007/s00455-002-0050-y.
- 403 [28] V.N. Felix, S.M.A. Corrêa, R.J. Soares, A therapeutic maneuver for oropharyngeal
 404 dysphagia in patients with Parkinson's disease., *Clinics.* 63 (2008) 661–666.
 405 doi:10.1590/s1807-59322008000500015.
- 406 [29] M.M. Bahia, S.Y. Lowell, A systematic review of the physiological effects of the effortful

- 407 swallow maneuver in adults with normal and disordered swallowing., *Am. J. Speech. Lang.*
408 *Pathol.* 29 (2020) 1655–1673. doi:10.1044/2020_AJSLP-19-00132.
- 409 [30] S.M. Molfenter, C.-Y. Hsu, Y. Lu, C.L. Lazarus, Alterations to swallowing physiology as
410 the result of effortful swallowing in healthy seniors., *Dysphagia.* 33 (2018) 380–388.
411 doi:10.1007/s00455-017-9863-6.
- 412 [31] K. Takahashi, M.E. Groher, K. Michi, Methodology for detecting swallowing sounds.,
413 *Dysphagia.* 9 (1994) 54–62. doi:10.1007/BF00262760.
- 414 [32] P.E. Shrout, J.L. Fleiss, Intraclass correlations: Uses in assessing rater reliability, *Psychol.*
415 *Bull.* 86 (2005) 420.
- 416 [33] Y. Khalifa, J.L. Coyle, E. Sejdić, Non-invasive identification of swallows via deep
417 learning in high resolution cervical auscultation recordings., *Sci. Rep.* 10 (2020) 8704.
418 doi:10.1038/s41598-020-65492-1.
- 419 [34] J.M. Dudik, I. Jestrovic, B. Luan, J.L. Coyle, E. Sejdic, Characteristics of Dry Chin-Tuck
420 Swallowing Vibrations and Sounds, *IEEE Trans. Biomed. Eng.* 62 (2015) 2456–2464.
421 doi:10.1109/TBME.2015.2431999.
422