Supplemental Material S1. Logistic regression using multiply imputed data and logistic regression with alternative EAT-10 categorical cutoff at 15.

Logistic Regression Using Multiply Imputed Data

The complete dataset contained 29 variables across 513 respondents, with 17.5% missingness. Because respondents with missing data may have differed from those without missing data on some unobserved variable/s, regression results from complete cases (Questions 3 and 4 in the main article) were compared to results using multiply imputed data. Data were replaced using multiple imputation by chained equations using the *mice* 3.8 package in R (van Buuren & Groothui-Oudshoorn, 2011). Multiple imputation (Rubin, 1987) is a useful method for handling missing data (especially in questionnaire or survey data) because it can improve the accuracy and power of analyses compared to methods such as listwise deletion (which may lead to biased results). To answer Questions 3 and 4, five multiply imputed datasets of parameters of interest were estimated, and subsequently pooled using Rubin’s rules.

Question 3. Do symptoms of SERF among community-dwelling older adults predict dysphagia risk?

To determine whether SERF predicted dysphagia risk, a logistic regression was run on all respondents ($n = 513$) after first multiply imputing missing data, which were then combined according to Rubin’s rules. The categorical EAT-10 variable was transformed prior to imputation, as recommended by von Hippel (2009). All original predictor variables were included in the model (SERF scores, age, gender, sarcopenia, malnutrition risk, general fatigue, quality of life, and recruitment method). SERF was the only significant predictor of dysphagia risk on the EAT-10 ($B = 0.20$, $p < .001$). Table 10 shows B values and their significance. Pooled estimates from multiply imputed data were compared to an analysis of complete cases ($n = 417$), with similar results (see main article).

Table S1. Pooled estimates across predictor variables for dysphagia risk.

Variable	*B*	Std. error	*z* value	*p*
SERF	0.20	0.02	7.21	< .001*
Age	0.03	0.03	0.84	.41
Gender	–0.24	0.30	–0.81	.42
SARC-F	–0.01	0.12	–0.05	.95
Self-MNA	–0.07	0.09	–0.82	.41
FACIT	0.03	0.02	1.15	.25
OP-QOL	0.02	0.02	0.57	.57
Recruitment Method	0.13	0.35	0.38	.70

Question 4. Do symptoms of SERF among community-dwelling older adults predict risk of malnutrition?

To determine whether SERF predicted categorical malnutrition risk, a logistic regression was run on all respondents (n = 513) after first multiply imputing missing data, which were then combined according to Rubin’s rules.

The model controlled for age, gender, dysphagia risk, sarcopenia status, general fatigue, quality of life, and recruitment method. Significant predictors for malnutrition risk included SERF (B = .05, p = .02), general fatigue on the FACIT (B = .06, p = .01), and quality of life on the OPQOL (B = –.04, p = .04. Table 2b shows B values and their significance. These pooled estimates from multiply imputed data were compared to the analysis of complete cases (n = 417) for comparison, with similar results (see main article).

Table S2. Pooled estimates across predictor variables for malnutrition risk.

Variable	*B*	Std. error	*z* value	*p*
SERF	–0.05	0.02	–2.42	.02*
Age	–0.02	0.03	–0.57	.58
Gender	–0.19	0.24	–0.81	.42
SARC-F	0.06	0.09	0.61	.55
EAT-10	–0.02	0.02	–0.73	.47
FACIT	–0.06	0.02	–2.61	.01*
OPQOL	0.04	0.02	2.07	.04*
Recruitment Method	0.14	0.26	0.53	.60

Logistic Regression With Alternative EAT-10 Categorical Cutoff at 15

There is some evidence to suggest that individuals with EAT-10 scores > 15 are significantly more likely to have aspiration compared to individuals with scores ≤ 15 (Cheney et al., 2015). Therefore, Question 3 was also tested using a cutoff score of 15 to determine whether SERF predicts dysphagia risk. The model again controlled for age, gender, sarcopenia status, nutritional status, general fatigue, quality of life, and recruitment method. When this model was run on 5 multiply imputed and pooled datasets, the two significant predictors of aspiration risk were SERF (B = 0.11, p < .001) and recruitment method (B = –1.86, p < .001).

Pooled results from multiply imputed data were compared to an analysis of complete cases (n = 417). At a cutoff score of 15 in complete cases, 395 respondents fell into the “No dysphagia risk” category, while only 22 participants fell into the “Dysphagia risk” category. Despite the poor distribution, the model was run and found to be significant, $X^2(8) = 87.8$, $p < .001$, pseudo $R^2 = 51.0$. Overall, 95% of participants were correctly classified, however, classification for the “Dysphagia risk” group was poor (41% correctly classified).

SERF and recruitment method were the only significant predictors of dysphagia risk on the EAT-10 (SERF *OR* = 1.2, 95% CI[1.13, 1.34], $p < .001$, recruitment method *OR* = 0.19, 95% CI [0.05, 0.65], $p = .01$). For every unit increase in SERF score, the odds of being at risk for dysphagia increased by 21%. The odds of social media respondents having EAT-10 scores > 15 were 81 times higher than Prolific respondents having EAT-10 scores > 15.

Using an EAT-10 cutoff at 15 did not change the overall findings of SERF being a strong predictor of dysphagia risk on the EAT-10, however, using a cutoff score of 3 (see main article) improved the percent of correctly classified respondents, and had a better distribution across categories.

References

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