Supporting Table 2. Prediction results when selecting features via differential language analysis.

features	**Gender** *accuracy*	**Age** *R*	**Extraversion** *R*	**Agreeableness** *R*	**Conscientious.** *R*	**Neuroticism** *R*	**Openness** *R*
LIWC	77.7%	.65	.25	.25	.29	.22	.28
Topics	**88.2%**	**.79**	**.34**	**.28**	**.34**	**.28**	**.39**
WordPhrases	**91.8%**	**.81**	**.37**	**.27**	**.34**	**.28**	**.40**
WordPhrases + Topics	**92.0%**	**.82**	**.38**	**.29**	**.35**	**.30**	**.41**
Topics + LIWC	**89.2%**	**.80**	**.35**	**.28**	**.34**	**.28**	**.40**
WordPhrases + LIWC	**91.8%**	**.81**	**.38**	**.28**	**.34**	**.29**	**.40**
WordPhrases + Topics + LIWC	**92.0%**	**.82**	**.38**	**.30**	**.35**	**.30**	**.41**

accuracy: percent predicted correctly (for discrete binary outcomes). R: Square-root of the coefficient of determination (for sequential / continuous outcomes). *LIWC*: *A priori* word-categories from Linguistic Inquiry and Word Count. *Topics*: Automatically created *LDA* topic clusters. *WordPhrases*: words and phrases (n-grams of size 1 to 3 passing a collocation filter). Bold indicates significant ($p < .01$) improvement over the baseline set of features (use of *LIWC* alone). Differential language analysis was run over the training set, and only those features significant at Bonferonni-corrected $p < 0.001$ were included during training and testing. No controls were used so as to be consistent with the evaluation in the main paper, and so one could consider this a univariate feature selection. On average results are just below those of not using *differential language analysis* to select features but there is no significant difference.