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Personalized State Anxiety Detection: An Empirical Study with Linguistic Biomarkers and A Machine Learning Pipeline

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***Abstract*— Individuals high in social anxiety symptoms often exhibit elevated state anxiety in social situations. Research has shown it is possible to detect state anxiety by leveraging digital biomarkers and machine learning techniques. However, most existing work trains models on an entire group of participants, failing to capture *individual differences* in their psychological and behavioral responses to *social contexts*. To address this concern, in Study 1, we collected linguistic data from N=35 high socially anxious participants in a variety of social contexts, finding that digital linguistic biomarkers significantly differ between evaluative vs. non-evaluative social contexts and between individuals having different trait psychological symptoms, suggesting the likely importance of personalized approaches to detect state anxiety. In Study 2, we used the same data and results from Study 1 to model a multilayer personalized machine learning pipeline to detect state anxiety that considers contextual and individual differences. This personalized model outperformed the baseline's F1-score by 28.0%. Results suggest that state anxiety can be more accurately detected with personalized machine learning approaches, and that linguistic biomarkers hold promise for identifying periods of state anxiety in an unobtrusive way.**

I. Introduction

Social anxiety disorder (SAD) is highly prevalent, impacting 13% of adults in the United States at some point in their lifetime [1]. Individuals with SAD fear and often avoid social interactions, or endure them with significant anxiety [2]. However, roughly 80% of individuals delay or avoid treatment [3], [4]. Digital interventions delivered to individuals via mobile technology (e.g., smartphones) in daily life can increase treatment access among individuals with SAD. "Just-in-time" adaptive interventions (JITAIs; [5]) are a good candidate to increase access to care. By providing individuals with treatment components when and where they need them, JITAIs have the potential to help socially anxious individuals navigate social situations more effectively in real time. Crucially, to deploy JITAIs, we need to detect when *socially anxious* people are in need of an intervention.

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Machine learning (ML) offers a computational solution to detect state anxiety status from digital biomarkers (i.e., passively sensed bio-behavioral indicators) [6]. In particular, using ML with linguistic biomarkers is a promising option for understanding social anxiety as this data can be passively collected without active user input and contains a wealth of psychological information [7].

Despite this potential, a limitation of much ML-based computational work with psychological data is its reliance on nomothetic approaches. Specifically, it has generally used one-size-fits-all approaches (e.g., modeling and reasoning about entire observed populations indiscriminately) [8], even though idiographic (i.e., person-specific) outcomes are typically of most interest to clinicians (e.g., a specific individual's risk of developing an anxiety disorder) [9]. At the same time, most personalized ML approaches require extensive data points from individuals, which is often impractical to collect (e.g., due to participant burden, low engagement, time and resource limitations) [10]. There are thus many challenges for ML models to efficiently and effectively detect state anxiety (e.g., model overfitting, inaccuracy, and bias) [11].

This study aims to develop a *personalized ML pipeline* that accounts for contextual and individual information to detect state anxiety. To this end, we propose a two-stage study. Study 1, an *empirical study*, examines the differences in linguistic biomarkers associated with state anxiety across social contexts and individual subgroups. In controlled dyadic Zoom conversations, we observe that socially anxious college students' (N=35 final sample) linguistic patterns significantly differ across experimentally manipulated contexts (one designed to be explicitly socially evaluative and one not explicitly socially evaluative) and clustered psychological-symptom severity subgroups. Based on these findings, in Study 2, we develop and test a *personalized ML pipeline* to detect state anxiety that accounts for contextual and individual differences using multi-layer fine-tuning training approaches. This pipeline hierarchically trains the model at the population, contextual, and individual levels by progressively adding new neural network layers and narrowing down the data samples grouped by contexts and individuals.

In summary, this paper makes the following contributions:

- We report evidence of significant linguistic differences between situational contexts and individual subgroups among socially anxious individuals, which suggests idiographic distinctions and motivated our ML models.
- We propose a multilayer personalized ML pipeline to detect state anxiety, which is able to hierarchically fine-

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tune a population-based model to capture contextual (i.e., social threat) and subgroup-based (i.e., psychological symptom severity) domain knowledge.

II. Empirical Study

A. Study Design

All study procedures were approved by the Institutional Review Board (IRB) of a large U.S. university and conducted under the supervision of a licensed clinical psychologist and researcher with expertise in anxiety disorders. We recruited 45 undergraduate participants with a Social Interaction Anxiety Scale (SIAS) score of 34 or above, indicating greater trait social anxiety (scale ranges from 0 to 80). Ten of the 45 participants did not complete the social experiences to be analyzed in this paper, leaving 35 participants eligible. The 35 participants had a mean age of 19.46 (SD = 2.09), and the majority were female (74.3%) and White (82.8%).

In the broader parent study, participants completed a series of social and non-social tasks involving different group sizes (i.e., alone, pairs, and groups of 4-6) and levels of experimenter-manipulated social threat. All study procedures were conducted virtually via Zoom. For the purposes of the present investigation, we focus on the two conversation tasks that participants completed in pairs (because the dyadic exchange allowed for clear evaluation of linguistic features). One conversation was explicitly evaluative and the other was *not* explicitly evaluative based on experimenter instructions (termed evaluative and non-evaluative, accordingly, for ease of reference). Specifically, we manipulated the level of social-evaluative threat present in the conversations: Prior to one conversation, participants were told that their partner would rate their social performance following the conversation (i.e., *evaluative*); prior to the other conversation, participants were told that they would *not* be rated (i.e., *non-evaluative*). During the two conversations, two participants discussed a randomly assigned topic for four minutes. The order of the two conversations was randomized.

B. Data Collection

Participants reported on their baseline and concurrent state anxiety (Def 1) during each of the social experiences via two brief surveys to report state anxiety levels (Def 2).

Definition 1: **Baseline and Concurrent State Anxiety**: Baseline state anxiety refers to the state anxiety level that participants report prior to learning about the upcoming social experience they will complete. Concurrent state anxiety refers to participants' most intense state anxiety *during* the social experience, as reported by each participant immediately after the experience ended. In this study we assessed participants' state anxiety via a Qualtrics survey by asking them to rate how anxious they felt on a five-point Likert scale from Very Calm (1) to Very Anxious (5).

Definition 2: **State Anxiety Status**: In this study, we aim to detect *state anxiety* status (i.e., status when the participants were in *high and/or elevated* state anxiety), as both represent times when individuals may benefit from a JITAI. Specifically, *high* state anxiety refers to periods when a participant reports either feeling anxious (4) or very anxious (5) during the concurrent stage. *Elevated* state anxiety refers to periods when the participants' concurrent anxiety is higher than their baseline anxiety, regardless of the particular score reported. See Figure 1, state anxiety oscillated during the study with notable elevation in the evaluative contexts (the right half).

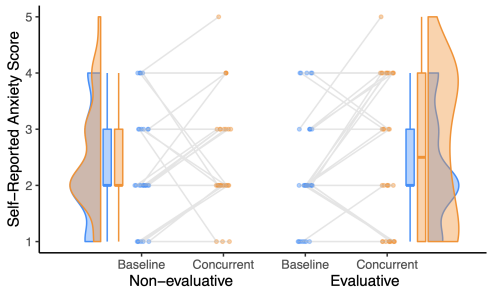


Fig. 1: Self-reported baseline v.s. concurrent state anxiety. Each point reflects an anxiety score reported by a participant.

Participants' *psychological symptoms* (in this case, self-reported trait anxiety and depression symptoms, and emotion regulation) were measured at the end of the study by four scales. The scales included the depression subscale from the Depression, Anxiety and Stress Scale (DASS; [12]) [13], the Social Interaction Anxiety Scale (SIAS; [14]), Brief Fear of Negative Evaluation scale (BFNE; [15]), and Difficulties in Emotion Regulation Scale - Short Form (DERS-SF; [16]).

The audio of the participants was recorded through Zoom. Otter.ai then transcribed the conversation text, identifying the start and end time points and the speaker for each sentence. The identified time points were used to segment and aggregate each participant's recordings sentence by sentence. Altogether, 55 samples of audio recordings and corresponding self-reported state anxiety were collected; 20 participants completed both the non-evaluative and evaluative sections (40 samples); due to the time limitation of the data collection, 7 participants only completed the non-evaluative experience (7 samples), and 8 participants only completed the evaluative part (8 samples).

C. Linguistic Biomarkers

TABLE I: Linguistic feature list with descriptions.

Domain	Feature	Description
Acoustic	Pitch	Mean and delta of voice frequency
	Energy	Mean and delta of voice intensity
	Zero-crossing rate	Mean and delta of the number of times the voice signal crosses the zero-axis
	Spectral center	Mean and delta of the voice spectrum center
Syntactic	Avg. word count	Average number of words per sentence
	Long sentence	Percentage of sentences with $>$ 15 words
	Sentence count	Total number of sentences spoken
Lexical	Pos. emotion	Number of words indicating positive sentiment
	Neg. emotion	Number of words indicating negative sentiment
	I-statements	Number of first-person pronouns
	You-statements	Number of second-person pronouns
	Negations	Number of negation words or phrases
	Stop words	Number of function words

We extracted linguistic biomarkers from speech audio and

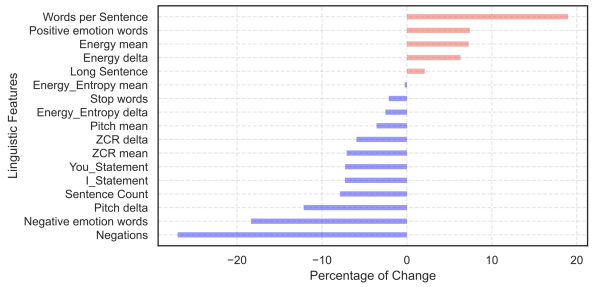


Fig. 2: Percentage loss (in blue) vs. gain (in red) for linguistic biomarkers between non-evaluative vs evaluative context.

transcripts in each sample, as a large body of literature has linked anxiety with linguistic biomarkers [7], [17]. We extracted *phonetic*, *syntactic*, and *lexical* domain features for each sample (Table I). To effectively model and measure participants' linguistic behaviors, we only extracted one-dimensional features verified by the existing literature.

D. Results

1) ***Situational Context Matters****:* First, we explored the differences in linguistic biomarkers between *non-evaluative v.s. evaluative* situational contexts with paired analysis on the 20 participants who completed both non-evaluative and evaluative experiences.

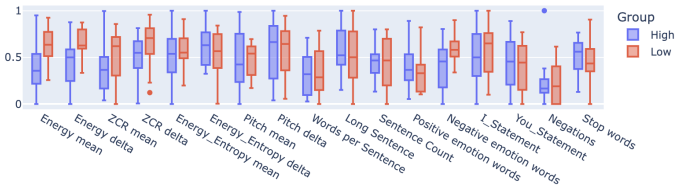
After normalizing each feature to a scale of 0-1 for comparison on a common scale, using paired analysis, we compared the percentage changes of linguistic biomarkers in the evaluative contexts compared to the non-evaluative contexts (see Figure 2). In the evaluative context, notably decreased linguistic biomarker scores included negations (-27.0%, p=0.306), pitch delta (-22.5%, p=0.018), negative emotion words (-18.4%, p=0.066), I-statements (-14.6%, p=0.396), zero-crossing rate (-11.7%, p=0.100), sentence count (-11.2%, p=0.087), zero-crossing rate delta (-9.6%, 0.050), and pitch mean (-8.7%, p=0.096). Increased biomarker scores between evaluative and non-evaluative contexts included words per sentence (+34.5%, p=0.015) and energy delta (+9.5%, p=0.171). The Wilcoxon signed rank test was used to test the p-values with $p<.05$ considered a reliable effect.

2) ***Individual Differences Matter****:* We then performed cluster analysis to aggregate participants according to their trait psychological scales by clustering the participants by their DASS, SIAS, BFNE, and DERS scales using the K-means algorithm. Individuals with similar trait symptom severity were gathered (i.e., similar score patterns on social anxiety and depression severity, and emotion regulation tendencies; henceforth called *symptom severity* for ease of reference [1]). To find optimal parameter K of K-means, we calculated the silhouette scores of K values from 2 to 5. The optimal K found is 2 (silhouette score=0.394), while the silhouette scores are 0.343, 0.373, and 0.364 when K are 3, 4, and 5. Selecting $K = 2$ to operate cluster analysis,

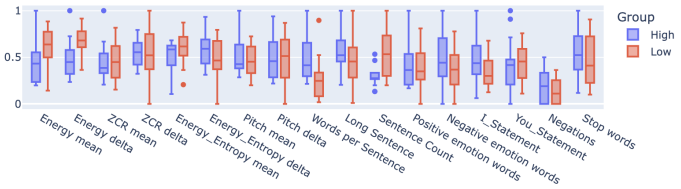
[1]Though we recognize DERS reflects a transdiagnostic vulnerability for emotional disorders, rather than a measure of symptom severity per se.

TABLE II: Profile of the 4 psychological scales among the two symptom groups. Abbreviation: Symptom=sx.

Measures	**High Sx (N=13)**		**Low Sx (N=17)**	
	mean	std	mean	std
DASS	69.16	10.31	51.13	7.67
SIAS	33.44	4.51	23.93	8.00
BFNE	58.12	6.27	41.93	5.75
DERS	15.36	5.05	12.27	5.02



(a) Non-evaluative context



(b) Evaluative context

Fig. 3: Distributions of 0-1 normalized linguistic features of clustered symptom severity subgroups in non-evaluative and evaluative contexts, respectively.

as profiled in Table II, the two clustered individual cohorts reflected two symptom severity groups. Group 1 (named high symptom severity) generally had high symptoms of social anxiety and depression (DASS and SIAS), fear of negative evaluation (BFNE) and difficulty with emotion regulation (DERS), whereas group 2 (named low symptom severity) had lower scores on those measures.

As shown in Figure 3, the two subgroups behaved differently in some aspects in linguistic. Specifically, the high symptom group generally had *lower* energy mean and delta, zero-crossing rate mean, energy entropy mean, pitch mean, as well as *higher* energy entropy delta, words per sentence, long sentence rate, and stop word rate in both contexts. Typically, in the evaluative context, the high symptom group had more *words per sentence*. Also, in the evaluative context, individuals with high symptom levels tend to use more negative emotional words, perhaps indicating a higher degree of distress, compared to those with low symptom levels. Moreover, high symptom individuals used more first-person pronouns than the low symptom group in the evaluative context. These patterns suggest that, in addition to individual and subgroup differences in behavior across contexts, certain behavioral patterns are more likely to be associated with evaluative social contexts than others.

III. Personalized Learning Pipeline

Sections II-D.1 and II-D.2 indicated there are behavioral differences between the two contexts and the two cohorts, suggesting that a personalized ML pipeline should ideally be tailored to the variability in social contexts and across persons/cohorts. We devised such a ML pipeline based on Multilayer Perceptron (MLP) model [18], which we term the Personalized State Anxiety Detector (**PSAD**).

A. Problem Formulation

Given the raw input data $D_p = \{d_1, d_2, \cdots, d_n\}$, where n indicates the number of linguistic views of D_p, of participant p, the task is to predict binary state anxiety status S_p (Definition 2). To achieve this, we proposed a framework that includes: 1) a set of biomarker extractors $\{f_1, f_2, \cdots, f_n\}$ to map different views of features into spaces $F_i^p \in \mathbb{R}^{m_i}$, where m_i is the dimension of features in view i; 2) a multiview fusion method that fused $F_1^p, F_2^p, \cdots, F_n^p$ into a hidden vector H_p; 3) applies a personalized classification model C_p to H_p that can be narrowed down by participant p, leveraging the contextual and individual information SC_p to predict S_p.

B. Personalized ML Pipeline Design

As shown in Figure 4, PSAD includes two components:

*1) **Multiview Featurization and Fusion**:* The pipeline first extracts multi-view biomarkers FS from the raw input data stream D while using domain knowledge. Then it fuses FS from different aspects/views with different domain-specific meanings (e.g, in our case, acoustic, syntactic, and lexical features) into one hidden vector H. Specifically, to model the contributions of different views' inputs, we assign learnable coefficients α_i to each view i and refine the coefficient weights during the training process; formally,

$$H = \sum_{i \in N} \alpha_i \cdot g_i(FS_i, \theta_{gi}) \tag{1}$$

where H denotes the fused vector of biomarkers, N is the number of different views, g considered a set of neural networks that maps FS from $\mathbb{R}^{m_i}$ to $\mathbb{R}^K$, K is the output dimension of H, and the θ_{gi} are the model parameters.

*2) **Multilayer Personalized Training**:* consists of a pre-trained global module and a local grouping-based fine-tuned module, leveraging of both population-based and personalized (i.e., accounting for situational contexts and individual differences) information from the data collection. Inspired by the idea of transfer learning [19], the training process incorporates one *global pre-training* set of layers for learning from the population domain and two *fine-tuning* layers for situational context and individual cohort domains, respectively. Firstly, in the global pre-training step. We train a global model M_G (i.e., $M_G(\theta_G, H)$), where θ_G is the parameter set of the model and H is all the samples, with output $\hat{S}$ based on the ground-truth state anxiety status S using a binary cross entropy objective loss function $BCE(\hat{S}, S)$. After optimizing $BCE(\hat{S}, S)$, the model parameter set θ_G is frozen as a globally *pre-trained* model for further training. Then, in the fine-tuning step, based on pre-trained M_G with frozen parameter set θ_G, we subsequently attach new layers to M_G (without its output layer) to adapt the model to fine-tuned M_L according to the specific clustered samples H_p by situational contexts and then by individual differences, where $p \in P$, P denotes the set of participants in a specific group. The resulting prediction is $\hat{S_p} = M_L(\theta_L, H_p)$.

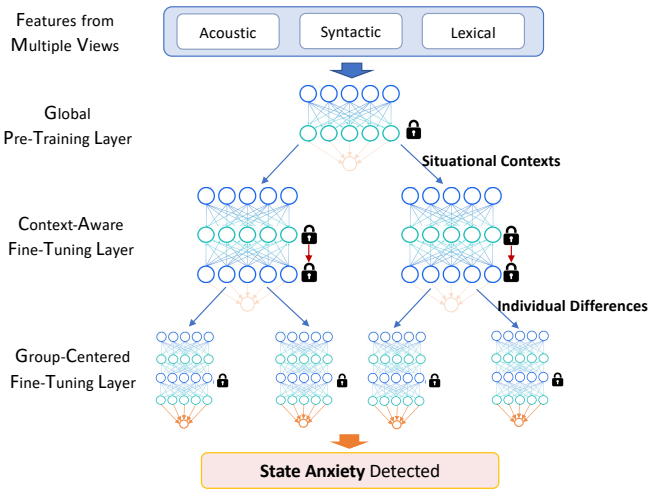


Fig. 4: Proposed multi-layer personalized ML pipeline.

C. Model Evaluation

We evaluated PSAD with the following research questions.

- **RQ1**: Does PSAD outperform generic (non-personalized) ML models?
- **RQ2**: How does the "multiview featurization and fusion" component optimize the model performance?
- **RQ3**: How does the "multilayer personalized training" component optimize the model performance?

We used the data collected in Study 1 to evaluate the ML pipeline. For the *context-aware layer*, the observations were divided by the situational contexts (i.e., non-evaluative and evaluative); for the *group-centered layer*, the sample was divided by high/low symptom severity subgroups.

We compared our PSAD with 5 ML methods, including K Nearest Neighbour (KNN), Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost), Multilayer Perceptron (MLP), Random Forest (RF) Classifier [20]. Evaluation metrics include accuracy, precision, and F1-Score.

We performed a cross-validation grid search to determine the best hyper-parameters (e.g., learning rate, and training epoch) for every baseline (i.e., each comparison method) and PSAD in a leave-one-sample-out cross-validation (LOOCV) manner. To make it a fair evaluation, 1) for the model with neural networks (i.e., PSAD and MLP), we set the number of layers to 4 (in PSAD, 2 for global training, 1 for context-aware fine-tuning, 1 for group-centered fine-tuning; in MLP, 4 layers in total) to guarantee that they have the same learning capability; 2) situational (non-evaluative or evaluative) and individual (high or low symptom severity) information was embedded into the feature space of the baseline models.

TABLE III: Comparison of model performance between proposed PSAD and the baselines (i.e., comparison methods).

Methods	Metrics (%)		
	Accuracy	Precision	F1 Score
KNN	50.90	50.94	50.91
SVM	41.81	41.79	41.81
XGBoost	58.18	58.36	58.09
MLP	58.18	58.22	58.18
RF	56.76	56.86	56.72
PSAD	**74.55**	**74.64**	**74.49**

TABLE IV: PSAD vs separately trained models

Subgroups	PSAD			Separated		
	Acc	Prec	F1	Acc	Prec	F1
High, Non-Eval	71.43	71.43	71.43	100.00	100.00	100.00
Low, Non-Eval	52.91	52.38	52.16	61.90	61.90	61.90
High, Eval	100.00	100.00	100.00	61.73	61.11	61.23
Low, Eval	69.10	69.09	69.07	45.56	44.44	44.44
Overall	**74.55**	**74.64**	**74.49**	63.64	63.64	63.64

1) RQ1: As shown in table III, PSAD shows improvements on every metric. Specifically, PSAD scored 74.55% in accuracy, 74.64% in precision, and 74.49% in F1-score, which improved at least 28.0% compared to baseline models. This indicates that the PSAD method can better detect the state anxiety status of highly socially anxious people.

We also compared PSAD to separately trained models for 4 subgroups to further evaluate its effectiveness. We found that PSAD performed significantly better in evaluative contexts and had a higher overall performance than the separate models. As shown in Table IV, our multilayer design showed a 10.85% improvement in performance due to its use of a hierarchical multilayer design.

2) RQ2: We conducted a feature ablation study to understand the effect of each linguistic view on model performance. We removed each view (acoustic, syntactic, and lexical) from the feature space and re-trained the model. The results, shown in Table V, indicate that the model performed best when equipped with all the features. Additionally, the learnable coefficient α for each modality shows the importance of each view of data: $\alpha_{acoustic}$ = 0.5071, $\alpha_{syntactic}$ = 0.5801, $\alpha_{lexical}$ = 0.8772. Both the ablation study and the coefficient α suggest that the lexical perspective is the most indicative of state anxiety, followed by the syntactic.

3) RQ3: To investigate the effect of the multilayer fine-tuning step, we conducted a second ablation study to understand how the context-aware and group-centered layers contribute to model performance. We removed one or two sublayers at a time and re-trained the model. The results, shown in Table VI, indicate that both the context-aware and group-centered considerations contribute to the final detection performance. However, the context-aware layer is more critical than the group-centered layer as the F1 score dropped to 63.56% when it was removed, compared to 66.81% when the group-centered layer was removed.

TABLE V: PSAD without (w/o) every single view.

Views	Metrics (%)		
	Accuracy	Precision	F1 Score
w/o Acoustic	62.35	61.82	61.56
w/o Syntactic	52.80	52.73	52.70
w/o Lexical	49.15	49.09	49.06
PSAD	**74.55**	**74.64**	**74.49**

TABLE VI: PSAD without (w/o) designed layers.

Methods	Metrics (%)		
	Accuracy	Precision	F1 Score
Only Global Layers	58.18	58.22	58.18
w/o Context-Aware Layers	63.66	63.64	63.56
w/o Group-Centered Layer	68.01	67.27	66.81
All Layers (PSAD)	**74.55**	**74.64**	**74.49**

IV. Discussion

A. Summary of Findings

Study 1 indicated that linguistic patterns vary across social contexts and individual symptom profiles. Specifically, we observed that participants had lower pitch and longer sentences on average in evaluative contexts, which is aligned with prior human behavior research [21]. Moreover, we found that individuals with higher anxiety symptom severity tended to exhibit specific linguistic characteristics, such as lower energy, zero-crossing rate, and pitch, longer sentences, and more stop words, particularly in an evaluative context. These patterns suggest that some groups' specific behavioral patterns are more likely to be associated with some social contexts than others, pointing to a person by context interaction (e.g., individuals with higher symptom severity may struggle to regulate emotions in contexts involving greater social threat [17]).

Study 2 advanced the ML model to be more personalized and learn more efficiently. Specifically, with PSAD, ML models can learn more personalized knowledge from limited human datasets in a hierarchical learning fashion, especially when highly socially anxious people are in an evaluative social threat context (RQ1). Both context-aware and group-centered information are crucial for the model's performance in digital state anxiety detection. In particular, the ablation study showed that the context-aware layer plays a more vital role in this detection (RQ2). Notably, acoustic, syntactic and lexical features all contribute to effective state anxiety detection. Results show that lexical features are the most indicative of state anxiety, which can inform future digital mental health practice (RQ3).

B. Implications for Future Practice

The present findings have multiple implications for state anxiety detection. First, linguistic characteristics are indicative of individuals' state anxiety. This, in turn, suggests that researchers working to build JITAIs may benefit from collecting linguistic information to identify opportune moments for intervention. Of course, determining how to do this in ways that are acceptable to the user and their contacts in terms of privacy, confidentiality, intrusiveness and other ethical issues is paramount. Second, personalizing prediction models by

using information about the individual's emotional health and symptoms, and their current social context helps us better detect the phenomenon of interest. Thus, future JITAI work would likely benefit from incorporating both individual differences and contextual features into prediction models. Third, our findings indicate that there is heterogeneity in terms of how linguistic features relate to state anxiety. That is, not only did linguistic features vary across evaluative and non-evaluative contexts and across symptom severity groups, but accounting for this variability in personalized models aided our prediction of state anxiety. This is in line with prior work suggesting that emotional states may not have a distinct 'fingerprint' and may instead relate to physiological data differently based on features of the individual in a particular situation [22]. At the same time, our findings suggest that clustering individuals based on psychological constructs (achieving a middle-ground between nomothetic and idiographic approaches) allows us to obtain valuable information about state anxiety beyond individuals. Future work aimed at detecting potential JITAI targets would benefit from considering cluster-based semi-idiographic methods to optimize prediction.

C. Limitations and Future Directions

Our study has several limitations, which point to opportunities for future research. Our analyses were limited to the two social contexts and the two subgroups among a small sample of university students. As such, our findings may not generalize to other individual differences, contextual features, and populations. Future work should examine these questions across different contexts (e.g., in-person vs. virtual interactions) and individual differences (e.g., gender identity, age). Also, as noted, even though linguistic data may help researchers improve state anxiety detection, there are many privacy concerns which could impact participants' willingness to use the technology. This is a concern researchers should keep in mind and they should ensure they are using secure methods, discussing concerns with participants, etc.

V. Conclusion

This paper tested the ability of personalized (vs. one-size-fits-all) ML approaches to detect state anxiety from linguistic biomarkers. Then, we proposed a personalized ML pipeline which progressively trains the model according to different domain knowledge (i.e., contextual and subgroup). We believe our personalized method may have considerable clinical utility relative to nomothetic ML approaches, and provide novel insights into how to optimize detection of key mental health outcomes.

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