Vocal Stress Diary: A Longitudinal Investigation of the Association of Everyday Work Stressors
and Human Voice Features

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Abstract

The human voice conveys plenty of information about the speaker. A prevalent assumption is that stress-related changes in the human body affect speech production, thus affecting voice features. This suggests that voice data may constitute an easy-to-capture measure of everyday stress levels and can thus serve as an early warning signal of stress-related health consequences. However, previous research is limited (i.e., has only induced stress through artificial tasks; has investigated only short-term or extreme stressors), leaving it open to whether everyday work stressors are associated with voice features. As such, our participants (111 working individuals) took part in a one-week diary study (Sunday until Sunday), where they provided voice messages and self-report data on daily work stressors. Results showed that work stressors were associated with voice features such as increased speech rate and voice intensity. We discuss theoretical, practical, and ethical implications regarding the voice as indicator of psychological states.

Keywords: stress, human voice, diary study, work stressors, well-being, multivariate Bayes analyses

Statement of Significance

With the ubiquity of smart devices (e.g., smartphones, smart speakers like Amazon's Echo), the human voice becomes an interesting source of information. In fact, it conveys information about people ranging from personality to emotional states. One of the most prevalent hopes is that the voice can become an early indicator of potentially problematic stress levels, which are one of the most universal causes for health issues. This paper shows that everyday work stressors (e.g., time pressure, social conflicts) may indeed affect voice features (e.g., speech rate). Thus, changes in the voice may, in future, help stress measurement and may serve as an early warning signal for high stress levels. We emphasize that it is necessary to consider the ethical and legal implications of our findings, as voice data is easily accessible and can allow us to draw insights about individuals, but that these should be drawn with consent and caution.

Introduction

The voice conveys rich information about the speaker. Voice features like pitch and speech rate are associated with speakers' age (Ptacek & Sander, 1966), sex (Lass et al., 1980), emotional states (e.g., Scherer, 2003), and disorders (e.g., depression; Mundt et al., 2007). Particularly prevalent is the assumption that changes in voice features allow inferences about an individual's stress levels (Schuller, 2018; Slavich et al., 2019), thus providing a potentially objective measure of stress, with stress being broadly defined as emotional, mental, and physiological strain in response to a real or perceived demand or threat (Goodday & Friend, 2019). Given the ubiquity of wearable technologies and microphone sensors in smartphones and smart speakers (e.g., Amazon's Echo), it could be possible to gather longitudinal voice data that provide insight on human stress levels (Goodday & Friend, 2019; Slavich et al., 2019). Considering that stress is a universal cause of health problems (Hassard et al., 2018), this could help to monitor everyday impact of stressors and facilitate early stress detection potentially contributing to better well-being (Slavich et al., 2019).

The predominant theoretical rationale behind the assumption that stress influences voice features is that stress, resulting from stressors, impacts the (para-)sympathetic system and the hypothalamic-pituitary-adrenal (HPA) axis (Giddens et al., 2013). Stress is characterized by high physiological arousal associated with activation of the sympathetic system and the HPA axis stimulating production of adrenalin and cortisol (Peifer et al., 2014). In response, this should increase muscle tension (e.g., in neck, throat), which affects the tension of the vocal chords, and can lead to a higher respiratory rate and bronchodilatation, which increases the pressure with which air flows through the glottis. This should influence speech production and thus voice features (Giddens et al., 2013, Scherer, 1986). For instance, a higher tension in the vocal chords increases the voice's fundamental frequency (or pitch); bronchodilatation and a higher respiratory rate can

increase voice intensity and speech rate (see Zhang, 2016, for details on the mechanics of speech production).

Several studies support associations between stressors, stress, and voice features (for reviews see Giddens et al., 2013; Giannakakis et al., 2019). For instance, Giddens et al. (2010) induced stress in 12 participants through pain (putting participants' hands in ice water) and found a higher speech rate in a speech production task (i.e., repeating syllables). Most previous work induced stress through artificial tasks – for example, Mendoza and Carballo (1998) let 82 students perform different cognitive tasks (e.g., spelling backwards) with the information that performance in these tasks would affect their course grades and found increased fundamental frequency and lower jitter and shimmer (measures of voice quality) compared to baseline tasks. Scherer et al. (2002) captured 100 male speakers' voices who had to speak using standardized sentences during a multi-tasking experiment (conducting a deduction task while having to react to auditory signals) and found increases in fundamental frequency and speech rate. Beyond artificial tasks, there have been few attempts to capture stress in more realistic settings. Pisanski et al. (2018) induced stress by having 80 participants give a speech and interrupting them to count backwards. They found a higher fundamental frequency during the task compared to baseline voice measures. Lu et al. (2012) induced stress in 14 participants by having them first conduct a job interview and then recruit strangers for studies. The authors trained machine learning classifiers to separate baseline voice from the voice in the stressful tasks and reported a classification accuracy between 66 and 83 percent (depending on the feature set), with fundamental frequency and speech rate being two of the most important features for classification. Finally, previous research examined extreme stress situations – for example, Ruiz et al. (1990) investigated conversations between pilots before a plane crash and found increases in fundamental frequency.

Whereas such findings have been used to draw the optimistic conclusion that the voice is a valid indicator of everyday stress levels (Slavich et al., 2019; Schuller, 2018), some researchers (e.g., Goodday & Friend, 2019; Mohr et al., 2017) have cautioned that there is crucial work to be done before generalizing to everyday stress experiences. We agree that it is a leap to conclude that based on research so far, the voice can be used for everyday stress assessment. Although Giddens et al.'s (2013) and Giannakakis et al.'s (2019) reviews report that research consistently finds increases in fundamental frequency, their results are less conclusive regarding speech rate and voice intensity. Furthermore, the relation between stress and measures of voice quality (e.g., jitter) is even less clear. Moreover, these reviews reveal research gaps. First, previous studies predominantly evoked stress through stressors that might not be comparable to everyday stress experiences, by inducing pain (Giddens et al., 2010) or having participants complete artificial tasks (Mendoza & Carballo, 1998). Second, most previous studies evoked short-term stress (e.g., Lu et al., 2012; Tolkmitt & Scherer, 1986; for similar criticism see Goodday & Friend, 2019), whereas everyday stressors affect people over days and weeks (Bakker & Demerouti, 2017). Third, previous studies investigated effects of extreme stressors (Ruiz et al., 1990) – stressors that only seldom occur in everyday life (DeLongis et al., 1982). Finally, research has investigated isolated contexts and experimentally manipulated specific stressors (e.g., Pisanski et al., 2018), whereas everyday stress is caused by various stressors (e.g., time-related, interpersonal). Thus, an analysis on the association of everyday stressors and voice features is needed.

The next crucial step for research on the association between stress and the voice is to show whether everyday stressors captured longitudinally and in naturalistic settings are associated with voice features (Giddens et al., 2013; Goodday & Friend, 2018). Only if we can show this association outside the laboratory, in low-risk situations, and with everyday stressors, we can conclude that voice can indeed become a useful indicator of everyday stress experiences. As such,

we conducted a one-week diary study with working individuals where we posit that work-related stressors, beyond other intra-individual variations related to changes in voice features (e.g., mood-induced effects on physiological arousal; Scherer, 2003), will be associated with changes in voice features. Specifically, in line with possible stress-related influences on the body (e.g., higher respiratory rate, bronchodilation, higher muscle tension) work stressors will be associated with higher fundamental frequency (similar to what was previously found, Giddens et al., 2013; Giannakakis et al., 2019), voice intensity, and speech rate. Given that research to date on the relationship between voice quality (e.g., jitter, shimmer) and stress is inconclusive (Giannakakis et al., 2019; Giddens et al., 2013), we captured voice quality measures without clear hypotheses regarding their relation to work stressors.

Method

The study procedure, measures, and analyses plans of data collection waves for this study were preregistered under <https://aspredicted.org/blind.php?x=si2w8w> and <https://aspredicted.org/blind.php?x=8nb3gj>. We set up two different preregistrations as each wave of data collection differed slightly. Specifically, the study procedure was parallel for the two waves of data collection with the exception of participants responding to additional explorative questions in the second wave (i.e., daily hours of sports, sports activity, and participants' coping style). Furthermore, the second wave of data collection was extended for an additional week. In this additional week, participants were randomly assigned to two experimental conditions. In one condition, participants were provided with information on stress and in the other they conducted progressive muscle relaxation before recording the voice messages every day. However, week two of the second wave of data collection resulted in a low number of participants completing the study and thus we decided to only use data from the first week of data collection.

Sample

Over both waves of data collection, we intended to collect as many participants as possible, with a minimum of 90 participants. This study was advertised as a diary study on the topic of well-being at work and explicitly targeted working individuals who work at least part-time. We advertised this study on different social media platforms, on campus of a medium-sized German university and in the downtown area of a medium-sized German city, and contacted participant pools of working individuals via email.

Overall, 166 people agreed to participate. For the final dataset we only included participants who indicated they usually work more than 18 hours a week (indicating that they work at least part-time; we excluded 14 participants due to this criterion) and participants who provided data on four or more days (we excluded 37 participants due to this criterion). Additionally, we excluded 4 participants because they reported that they had filled out the study on separate days when they had actually responded to the study several times on a single day. Furthermore, we checked whether participants followed the instructions to respond after work (or whether they responded, for instance, in the morning before work) and excluded 56 days from the final dataset where participants did not follow the instructions. The final sample consisted of $N = 111$ German participants (65.77% female). Within this sample, 10 participants participated on four days, 13 participants on five days, 28 participants on six days and 60 participants on all seven days.

Participants' mean age was about 32.96 years ($SD = 10.90$, range: 19 to 59), and they worked on average 37.30 hours a week ($SD = 8.89$). Participants were from a variety of professional backgrounds, with 24 percent of participants working in healthcare and medical professions, 11 percent in administration, 11 percent in consulting, 10 percent in research, 6 percent in the service sector, and 5 percent in engineering. For the rest of participants, less than 5 percent

worked in areas such as HR, IT, automotive, banking, or insurance, respectively. Participants were offered 25 Euro for participation.

Procedure

This study was approved by the main author's research institution's ethics committee. The study followed a longitudinal design over one week (Sunday until Sunday) with seven measurement occasions for each participant, excluding Saturdays, as those are more likely to be working days compared to Sundays.¹

The entire study was conducted online and participants used their personal smartphone devices. Each day of the study consisted of two parts: participants sent voice messages where they responded to a set of four questions and completed a set of daily self-report measures. After participants stated their interest in participating via email, we provided them with an overview of the study procedure and the technical details to be aware of within this study. Specifically, we provided participants with a set of instructions to follow each day. First, participants were informed that within this study, they will be asked to respond to a series of questions after work on every day of the week, optimally soon after finishing work. Second, they were instructed to start this study on a Sunday, during a week where they did not have vacation, and optimally during a week where there was no official holiday. Third, they were instructed to set a reminder in their calendar for each day of the week that should remind them of the study after finishing work. Fourth, participants received instructions on how to prepare themselves every day prior to study participation. Participants were informed that, before they start the study each day, they should find a quiet place at home where they can take part in the study. They were instructed to use the same room each

¹ For one wave of data collection, we gathered data on Saturdays but decided to not use Saturday measurements in the analyses to keep the waves of data collection comparable.

time and to use a room where there is no obvious echo. They were also instructed on how to generate the voice messages (i.e., put their mobile phone about ten centimeters from their mouth and speak directly into the microphone).

Fifth, participants received a mobile phone number. With this number they reached a chatbot through a messenger app. We used the app AutoResponder (Kosmala, 2018) to program this chatbot. Sixth, participants received information on how to interact with the chatbot (together with a picture showing a sample conversation with the chatbot). The chatbot guided participants through a set of four questions where participants were asked to respond to via voice messages. Those questions were designed and pretested so that responses to all four questions would result in about five minutes of voice recordings per day. With this, we followed Lu et al.'s (2012) methodology who analyzed about four minutes of voice recording in their study to automatically derive voice features from those recordings. Accordingly, we decided that aiming for five minutes of voice recordings would balance the tradeoff between receiving enough voice data to reliably analyze daily voice features without overtaxing participants. At the start of participants' conversations with the chatbot, they were instructed to generate an individual key phrase and send this phrase to the chatbot via a text message in the messenger app. The chatbot then automatically responded to participants with further instructions. The chatbot instructed participants to send a key word that triggered the first question of the day for participants.

The first question each day was: "How was your day? Please respond to this question with as much detail as possible. Report about your day from the time you woke up until the time you started the study." (Note that all questions and instructions are translated from German). Participants were instructed to respond to this question via a voice message that was at least two minutes long. Additionally, participants were asked, after sending the voice message, to send another key word to the chatbot. This key word triggered the second question which was: "What

was the highlight of your day?” The same procedure was repeated for the third question, “What didn’t you enjoy about your day? If you cannot think about a negative experience: Please describe today’s most demanding event.”, and for the fourth question, “What are your plans for tomorrow? It can also be simple plans (e.g., go to bed early). Additionally, please report on whether you were able to follow through on your plans for today.” For questions two through four, participants were instructed to record a one-minute voice message. After responding to the last question, participants were instructed to send another key word to the chatbot to which the chatbot responded with a link to an online survey platform where participants responded to the self-report measures. This procedure was repeated each day. Within the online survey tool, participants first reported the key phrase they generated in the beginning of the study which enabled us to match voice recordings and survey information. Only on the first Sunday, participants reported their age, sex, usual working hours per week, their profession, and long-term stressors. On each day, participants reported their positive and negative mood, everyday work stressors, their working hours that day, as well as their perceived stress.

Measure

Items used in this study were administered in German. The English version of the items can be found in Supplemental Table S1. We chose those measures as the respective constructs have been shown to be associated with human voice features in previous research.

Measure on Only the First Sunday

Long-term stressors. As long-term stressors (like everyday stressors) might contribute to changes in voice features, we measured participants’ long-term stressors once on the first Sunday. Specifically, participants, on a scale from 1 (not at all) to 5 (extremely), responded to six items taken from the German Stress Coping Inventory (Satow, 2012) with the instruction “How much strain did you experience because of the following issues over the last months or weeks?” The

issues covered debt and financial problems, health issues, housing and moving, performance pressure or problems at work, demands of friends, family, or the partner, as well as own expectations and demands.

Daily Measures

Positive and Negative Mood. Mood can affect voice features (Scherer, 2003). We thus measured participants' mood using ten items from the German short form of the International Positive and Negative Affect Schedule Short Form (I-PANAS-SF; Krohne et al., 1996; Thompson, 2007; Watson, 1988). For both positive and negative mood, the scale includes five items. Participants responded on a scale from 1 (not at all) to 5 (extremely) and we used the following instruction "This scale consists of a number of words that describe different feelings and emotions. Read each item and indicate to what extent you feel this way at the present moment." A sample item for positive mood was "Active", a sample item for negative mood was "Upset."

Perceived Stress.² We measured perceived stress with the item "At this moment, I feel stressed" (see Metzenthin et al., 2009, or Watson, 1988, who used similar one-item measures for perceived stress). Participants responded to this item on a scale from 1 (not at all) to 7 (extraordinarily).

Everyday Work Stressors. To measure everyday work stressors, we used the German version of the Daily Stress Inventory (Brantley et al., 1987; Traue et al., 2000). The original version of this inventory consists of 58 statements. In order to not overtax participants, we only used 16 items which we adapted to increase their relevance to everyday work experiences. However, after the first wave of data collection, we realized that for the items "I was at work although I was sick.",

² We also measured perceived relaxedness but only use perceived stress in our analyses as this more directly reflects perceived stress.

“I stayed late at work”, “Someone did not fulfill an agreement”, “I was competing with someone else”, and “I received bad news” there was nearly no variance in responses to reasonably use them within the everyday work stressors scale. In order to reduce everyday study duration, we decided to remove those items for the second wave of data collection. Therefore, our final measure of everyday work stressors used in our analyses included 11 items. Sample items were “I had to work longer than intended”, “I did not understand a work task”, and “I was criticized or insulted”. Participants responded to these items on the German version of this scale from 1 (did not occur) to 8 (it was unbearable).

Daily Working Hours. Participants were instructed to report how many hours they worked on the respective day.

Voice Features. In order to extract participants’ voice features, we used the software PRAAT (Boersma & Van Heuven, 2001; Boersma & Weenink, 2019), a software commonly used for voice analysis throughout disciplines, including the context of the association of stress and voice (e.g., Sondhi et al., 2015). First, we extracted participants’ voice recordings from the mobile phone where the chatbot was installed on. We added the key phrase participants generated in the beginning of their individual study procedure to folders where we saved the voice recordings to match the recordings to online self-report data. Using PRAAT, we then automatically extracted voice features from the recordings. We chose to extract the following voice features that have commonly been measured in previous studies on voice, stressors, and stress (Giannakakis et al., 2019; Giddens et al., 2013): fundamental frequency, voice intensity, speech rate, jitter, and shimmer. Fundamental frequency was measured in Hertz. Voice intensity was measured in decibel. Speech rate was measured in syllables per second. Jitter measures short-term changes and irregularities in fundamental frequency. Shimmer measures short-term changes and irregularities

in voice intensity. For each of those features, we calculated the weighted mean (weighted for the duration of the respective voice recording) over the four daily voice recordings.

Data Analyses

All measures were included in the main analyses reported in the results section. Of focal interest for our study was the relation between everyday work stressors and voice features as well as perceived stress and voice features. All other variables were included because they are biological determinants of voice features (sex, age; Lass et al., 1980; Ptacek & Sander, 1966), because they have been shown to affect voice features (positive and negative mood; Scherer, 2003), or because we considered them to be control variables (long-term stressors, working hours, Sunday vs. Workday).

For all measures consisting of more than one item, we calculated the mean of those items and used the resulting mean in the analyses. Our data were longitudinal, multilevel and we had multiple dependent variables (i.e., voice features). For this longitudinal, multivariate, multilevel structure of our data, we determined that the most appropriate option to conduct our analyses was a Bayesian mixed model. Analyses were conducted in R (Version 3.6.3) using the *brms* package (Version 2.14.4, Bürkner, 2017) to fit the Bayesian mixed model. In this Bayesian mixed model, we included fundamental frequency, voice intensity, speech rate, jitter, and shimmer as dependent variables. We included participants' sex, age, daily working hours, whether it was a work day or a Sunday, long-term stressors, positive and negative mood, perceived stress, and everyday work stressors as predictors on the population level (or in frequentist terms: as fixed effects). We also included the interaction between everyday work stressors and perceived stress as a predictor in our analyses due to the fact that this additional subjective appraisal of stressors could fundamentally change the association between stressors and voice features (Scherer, 1986). Thus, including this interaction as a predictor should account for the fact that the effects of everyday stressors on voice

features might be exacerbated among participants with high perceived stress. We estimated varying intercepts for the voice features for each participant (random intercepts).

For predictors measured on a continuous scale that were only gathered once (i.e., age, long-term stressors), we used the grand-mean centered version of those predictors. For predictors measured on a continuous scale that were measured every day, we included the person-mean centered version of this measure. This way, results can be interpreted as deviations from the person mean for a respective predictor and criterion. We additionally included the grand-mean centered person mean of the predictors measured on a continuous scale that were measured every day. This was done to also account for between-person deviations in those predictors over the course of the week. All these variables were z-standardized before estimating the model.

Results

As a descriptive overview over our measured variables, Table 1 presents descriptive statistics of the variables and their correlations. As a measure of reliability, we report McDonald's omega.

Results for the Association between Stress and Voice Features

The following reporting of results is based on Table 2 and Figure 1. We report on findings that relate to our main research question (i.e., relating to the association between stressors, stress, and voice features). Specifically, we report on findings where the 95% credibility interval does not include zero and on findings where zero is not included in the 66% credibility interval. In the latter case we emphasize that those results show weaker evidence for an association adding the term “tendency” in the reporting. Note that unlike frequentist confidence intervals, credibility intervals indicate the range in which the respective estimates lie with a 95% probability, based on the current data and prior distributions (see supplemental material for information on the prior distributions).

The main question of our study was to investigate the relation between everyday work stressors, stress, and voice features. With regard to everyday work stressors, the clearest associations were found for voice intensity $b = 0.38$, 95% CI [0.18,0.58], and speech rate, $b = 0.03$, 95% CI [0.01,0.04], such that both were higher with more intense work stressors. There was also a tendency towards a higher fundamental frequency, $b = 0.69$, 95% CI [−0.23,1.61], and a tendency towards a negative association with shimmer, $b = -0.08$, 95% CI [−0.16,0.01]. Furthermore, perceived stress showed tendencies towards being associated with lower voice intensity, $b = -0.19$, 95% CI [−0.39,0.01], and higher shimmer, $b = 0.07$, 95% CI [−0.02,0.15]. Regarding the interaction between everyday stressors and perceived stress, results indicated that there was a tendency towards a higher speech rate, $b = 0.01$, 95% CI [0.00,0.02]. This means that on days where participants experienced more intense work stressors and at the same time perceived more stress, speech rate was even higher. In summary, these results support our proposition that everyday work stressors are associated with voice features. Moreover, the results are mostly in line with what can be expected with respect to stress-related consequences on speech production especially with regard to a higher voice intensity, higher speech rate and, less clearly, with regard to higher fundamental frequency. Additionally, these results indicate that there is a clearer association between everyday work stressors and voice features compared to perceived stress and voice features.

As an additionally noteworthy result, the clearest association with voice features was found for positive mood. Specifically, positive mood was associated with fundamental frequency, $b = 1.39$, 95% CI [0.66,2.15], voice intensity, $b = 0.40$, 95% CI [0.24,0.57], and speech rate (all higher), $b = 0.03$, 95% CI [0.01,0.04], as well as with lower jitter, $b = -0.05$, 95% CI [−0.09,−0.02], and shimmer, $b = -0.09$, 95% CI [−0.16,−0.02]. Initially, the findings for

positive mood might seem contradictory when considering that everyday work stressors were also associated with higher speech rate, voice intensity, and fundamental frequency. However, these voice features are not only associated with possible stress-related consequences on physiological activity but also with elevated physiological arousal in positive mood (Scherer, 2003) that is also reflected in the positive mood items (e.g., items such as “active”).

Discussion

Our diary study shows that everyday work stressors (e.g., time-related, interpersonal) are indeed associated with voice features. Thus, our study goes beyond studies manipulating single (artificial) stressors, studies investigating extreme stressors, or studies investigating short-term stress induction, and lends support to the notion that everyday work stressors can also lead to changes in the human body that affect speech production (Zhang, 2016). This is the crucial, and previously missing, next step for research on the potential use of the voice as an indicator of everyday stress (Goodday & Friend, 2019, Slavich et al., 2019).

Our findings imply that everyday work stressors were associated with higher voice intensity, higher speech rate, and a tendency towards a higher fundamental frequency and lower shimmer. First, this supports that everyday stress-related changes in the human body (i.e., high physiological arousal associated with activation of the sympathetic system and the HPA axis) influence the mechanics of speech production (e.g., muscle tension, bronchodilation, higher respiratory rate) in a way that may be measurable in voice features. Second, this supports previously found associations of various stressors and higher fundamental frequency (Giddens et al., 2013; Giannakakis et al., 2019). However, we go beyond previous work by showing this association for everyday stressors in a naturalistic setting and by showing that even under the consideration of other variables influencing the voice (e.g., mood), associations between voice features and everyday stressors remain stable. Third, our results support that voice intensity and speech rate may

increase through stressors, which is in line with assumed stress-related consequences on the body (Zhang, 2016). However, given ambiguous previous findings (e.g., regarding the associations between stressors and voice features other than fundamental frequency; Giannakakis et al., 2019), research needs to further uncover relations between stressors and voice features as well as possible situational (e.g., display rules) and individual moderators (e.g., coping style) (Scherer, 2003). Fourth, our findings imply that everyday stressors were more strongly associated with voice features than perceived stress. A tentative interpretation of this finding is that the voice may reflect bodily changes due to everyday stressors and may be less related to subjective stress perceptions. If this interpretation proves to be valid, this would support the potential of the voice as a possibly objective indicator of stress.

Before discussing further implications, we highlight one central limitation: We assumed that stress leads to bodily changes that affect speech production but did not measure these changes (e.g., effect of stressors on cortisol). We draw the conclusion that everyday stressors affect bodily changes in ways that align with our theoretical rationale because we found changes in voice features that speak in favor of the proposed changes. Due to the already demanding study design, we decided not to measure cortisol, although this could have increased the clarity of our results (see also Pisanski et al., 2016).

Nevertheless, our study demonstrates that everyday stress is associated with the voice. Specifically, we emphasize that there might be potential to use the voice as an indicator of people's everyday stress levels and as a possible easy-to-capture source of data to detect and prevent stress-related consequences on well-being (Slavich et al., 2019). Clearly, voice data will not be the only or the best indicator for stress – it may rather be used in combination with other stress-related measures (e.g., electrodermal activity, cortisol; Giannakakis et al., 2019) as an inobtrusive and easy-to-capture additional measure.

Several future steps need to be taken to make voice analysis more viable. For instance, our study only investigated a small range of possible voice features. We see potential in analyzing longitudinal datasets with machine learning approaches, which might detect more complex pattern than the ones we analyzed (Slavich et al., 2019). This would support Lu et al.'s (2012) preliminary results that the accuracy of machine-learning-based stress classification using voice features may be above 80% (although based on only 14 participants). Moreover, we restricted our analyses to voice features. Research that additionally decodes what people say will yield further insights into stress experiences (Schuller, 2018). This could provide information on coping mechanisms or interpretations of daily stressors (Scherer, 1986).

Finally, if we want to advance the assessment of psychological states via voice data, it is crucial to consider ethical and legal implications (Mohr et al., 2017; Slavich et al., 2019). For instance, regarding data privacy, we need to determine the circumstances under which smart speakers are allowed to analyze the voice for inferences about psychological states (Slavich et al., 2019). Furthermore, we need to discuss what inferences can or should be drawn from voice features. Even application scenarios that are intended to benefit well-being can be perceived as undermining human autonomy. For example, smart speakers could constantly measure stress without people being in control of what information they want to provide to the party that analyzes their data.

Successfully taking the next steps towards using speech and voice information as stress indicators could help prevent stress-related negative consequences for well-being (Hassard et al., 2018). We imagine sensor-based stress monitoring that serves to capture individuals' everyday stress levels. This data could be shared with therapists to enable them to ask about specific days or events where patients experienced stress, as reflected in their voice. Several companies (e.g., www.audeering.com; Engel, 2017) are working on applications using the voice as a lens to

psychological states. Our results support the potential of such applications for stress measurement, and hopefully serve to start discussions about the beneficial use of such applications.

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Table 1*Means, Standard Deviations, Reliabilities, and Correlations Using a Frequentist Approach.*

Variable	<i>M</i>	<i>SD</i>	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. Sex	1.66	0.48	.01 [-.18,.20]	.35 [.18,.51]	-.09 [-.27,.10]	.26 [.08,.42]	-.04 [-.22,.15]	.26 [.08,.43]	.26 [.08,.42]	.90 [.86,.93]	.15 [-.04,.33]	.09 [-.10,.27]	-.67 [-.76,-.55]	-.75 [-.82,-.65]
2. Age	32.96	10.90		-.08 [-.26,.11]	.02 [-.16,.21]	-.07 [-.26,.12]	.08 [-.11,.26]	-.05 [-.23,.14]	-.11 [-.29,.08]	-.14 [-.31,.05]	-.11 [-.29,.08]	.10 [-.09,.28]	.14 [-.05,.32]	.27 [.09,.44]
3. Long-Term Stressors	2.33	0.62			(.69) -.18 [-.36,.00]	.50 [.35,.63]	-.04 [-.23,.14]	.53 [.38,.65]	.54 [.40,.66]	.40 [.23,.55]	.04 [-.14,.23]	.15 [-.04,.32]	-.24 [-.41,-.06]	-.17 [-.34,.02]
4. Positive Mood	2.58	0.56				(.89) -.04 [.81,.92]	-.08 [-.22,.15]	-.11 [-.15,-.01]	-.07 [-.18,-.03]	.15 [-.26,.11]	.19 [.07,.22]	.17 [.12,.26]	-.10 [.09,.24]	-.09 [-.18,-.03]
5. Negative Mood	1.38	0.35				-.06 [-.13,.02]	(.82) [.71,.86]	.10 [.03,.18]	.56 [.51,.61]	.64 [.52,.74]	-.06 [-.14,.01]	.00 [-.08,.07]	.09 [.02,.16]	-.04 [-.12,.03]
6. Working Hours	5.29	1.80						.08 [-.11,.26]	.15 [-.03,.33]	.10 [.03,.17]	.04 [-.04,.11]	.06 [-.02,.13]	.04 [-.04,.11]	.05 [-.02,.12]
7. Perceived Stress	2.23	0.98					.21 [.14,.28]		.62 [.48,.72]	.00 [-.07,.08]	-.06 [-.13,.01]	.05 [-.03,.12]	.01 [-.07,.08]	.08 [.00,.15]
8. EWS	1.80	0.69			-.09 [-.16,-.02]	.40 [.34,.46]	.42 [.36,.48]	.34 [.27,.41]	(.89) [.84,.91]	.06 [-.02,.13]	.13 [.06,.20]	.18 [.11,.26]	-.03 [-.11,.04]	-.03 [-.10,.05]
9. Fundamental Frequency	163.55	43.53									.17 [-.02,.34]	.03 [-.04,.11]	-.70 [-.78,-.59]	-.06 [-.14,.01]
10. Voice Intensity	61.15	4.49								.15 [.07,.22]		.37 [.31,.43]	-.44 [-.50,-.38]	-.48 [-.54,-.42]
11. Speech Rate	3.05	0.28											.05 [-.14,.24]	.18 [-.01,.35]
12. Jitter	2.58	0.60								.20 [.12,.27]		-.22 [-.29,-.15]		.68 [.64,.72]
13. Shimmer	9.93	1.93										.05 [-.02,.13]		

Note. EWS = Everyday Work Stressors. The upper triangle of the table shows correlation coefficients between participants (multiple measurements were averaged). The lower triangle of the table shows correlation coefficients within participants. Numbers in parentheses indicate McDonald's ω reliability. For correlations, a 95% confidence interval is provided in square brackets. For McDonald's ω , square brackets indicate the range of reliability values between multiple measurements.

Table 2.
Results of the Bayesian Mixed Model

Predictors	Fundamental Frequency		Voice Intensity		Speech Rate		Jitter		Shimmer	
	<i>Estimates</i>	<i>CI (95%)</i>	<i>Estimates</i>	<i>CI (95%)</i>	<i>Estimates</i>	<i>CI (95%)</i>	<i>Estimates</i>	<i>CI (95%)</i>	<i>Estimates</i>	<i>CI (95%)</i>
Between Participants										
Female	190.57	[185.49, 195.42]	61.39	[60.11, 62.68]	3.09	[3.01, 3.17]	2.31	[2.17, 2.45]	8.89	[8.54, 9.25]
Male	111.42	[105.17, 117.36]	59.96	[58.35, 61.56]	3.04	[2.94, 3.14]	3.15	[2.98, 3.32]	12.04	[11.61, 12.47]
Age	-4.59	[-7.47, -1.69]	-0.50	[-1.35, 0.32]	0.03	[-0.02, 0.09]	0.08	[-0.00, 0.17]	0.54	[0.32, 0.75]
Working Hours	0.97	[-1.83, 3.74]	-0.27	[-1.12, 0.58]	0.01	[-0.05, 0.06]	-0.07	[-0.16, 0.01]	0.06	[-0.16, 0.28]
Long-Term Stressors	1.34	[-2.03, 4.65]	-0.01	[-1.11, 1.06]	0.09	[0.03, 0.16]	0.04	[-0.07, 0.15]	0.39	[0.11, 0.67]
Positive Mood	0.46	[-2.58, 3.35]	0.72	[-0.17, 1.58]	0.08	[0.02, 0.13]	0.02	[-0.07, 0.10]	0.03	[-0.19, 0.26]
Negative Mood	1.40	[-2.16, 4.95]	-1.26	[-2.52, -0.02]	-0.07	[-0.15, 0.00]	-0.02	[-0.15, 0.10]	0.11	[-0.21, 0.43]
Perceived Stress	-0.22	[-3.90, 3.51]	0.60	[-0.58, 1.86]	-0.02	[-0.09, 0.06]	0.02	[-0.10, 0.14]	-0.09	[-0.41, 0.22]
EWS	3.09	[-0.70, 6.85]	0.59	[-0.73, 1.94]	0.02	[-0.07, 0.10]	-0.07	[-0.21, 0.07]	-0.21	[-0.57, 0.13]
EWS × Perceived Stress	0.57	[-2.12, 3.25]	0.27	[-0.54, 1.10]	-0.05	[-0.10, 0.00]	0.01	[-0.08, 0.09]	-0.12	[-0.33, 0.09]
Within Participants										
Working Hours	0.83	[-0.36, 2.00]	-0.07	[-0.34, 0.20]	-0.00	[-0.02, 0.01]	0.02	[-0.03, 0.07]	0.02	[-0.09, 0.14]
Sunday vs. Workday	-0.16	[-2.55, 2.21]	0.17	[-0.39, 0.74]	0.01	[-0.03, 0.05]	-0.03	[-0.14, 0.08]	0.04	[-0.21, 0.29]
Positive Mood	1.39	[0.66, 2.15]	0.40	[0.24, 0.57]	0.03	[0.01, 0.04]	-0.05	[-0.09, -0.02]	-0.09	[-0.16, -0.02]
Negative Mood	-0.97	[-1.89, -0.03]	-0.03	[-0.23, 0.17]	0.00	[-0.01, 0.02]	-0.01	[-0.04, 0.03]	0.03	[-0.06, 0.12]
Perceived Stress	0.33	[-0.56, 1.24]	-0.18	[-0.39, 0.01]	-0.00	[-0.01, 0.01]	0.01	[-0.03, 0.05]	0.07	[-0.02, 0.15]
EWS	0.69	[-0.23, 1.61]	0.38	[0.18, 0.58]	0.03	[0.01, 0.04]	-0.02	[-0.06, 0.02]	-0.08	[-0.16, 0.01]
EWS × Perceived Stress	-0.20	[-0.85, 0.44]	-0.01	[-0.15, 0.13]	0.01	[-0.00, 0.02]	0.01	[-0.02, 0.04]	-0.00	[-0.06, 0.06]
Random Effects										
σ^2	0.07									
τ_{00}	0.03									
ICC	0.32									
N	111									
Observations	691									

Notes. EWS = Everyday Work Stressors. Including a categorical variable such as participants' sex in a Bayesian analysis can lead to a higher uncertainty in estimation for one sex category over the other (see McElreath, 2016 for an in-depth discussion on this issue). To prevent this, we included each sex category as a baseline which resulted in one estimate for male participants which acted as an intercept for male participants and another estimate for female participants which acted as an intercept for female participants.

Figure 1.*Results and Parameter Distributions of the Bayesian Mixed Model*

Notes. EWS = Everyday Work Stressors. Columns present the dependent variable, rows parameters of the model. Blue dots show the mean of the posterior distribution, thick lines the 66% quantiles, thin lines the 95% quantiles. The parameter Sunday vs. Workday shows the effect of a workday against a Sunday. The parameter sd(Intercept) shows the variation of intercepts between participants.

Supplemental File for Review 1

Supplemental Materials for Methods

Additional Notes on Data Analyses

Bayesian statistics require the specification of prior distributions. For regression coefficients we set this prior distribution to a normal distribution ($\mu = 0$, $\sigma = 3$). Thus, we expected regression coefficients to be in a range between ± 5.88 with a 95% probability. Female and male had separate intercepts for each voice features and the assumed prior distribution varied for different dependent variables in a range of reasonable values for the respective voice features (e.g., for fundamental frequency, the prior was set to a normal distribution with a mean of 150 and a standard deviation of 100, whereas for speech rate the prior was set to a mean of 3 and a standard deviation of 1). We used separate intercepts for male and female participants in order to ensure the same uncertainty when predicting female or male participants' voice features and in line with the suggestions by McElreath (2020). In contrast, using a single intercept for female participants and a dummy variable to capture the difference to male participants would have led to higher uncertainty in the estimates for male compared to female participants. Specifically, for female participants only the uncertainty for the intercept would have to be estimated but for male participants the uncertainty for the intercept and the dummy variable has to be estimated. Using sex-specific intercepts circumvents this issue.

In our analysis, we used a Bayesian regression model with two levels: The repeated measurements of participants' voice recordings (level one) were nested in the individual participants (level two). Thus, we estimated varying intercepts for every participant (in terms of frequentist statistics: random intercepts). The prior distribution of the standard deviation of these random intercepts was a t -distribution (as it is the default in the brms R package, Bürkner, 2017) with 10 degrees of freedom and a sigma of 10. Please note that results did not change substantially

when choosing other prior means and standard deviations. All dependent variables were expected to be normally distributed.

All analyses were conducted in R (Version 3.6.3) using the *brms* package (Version 2.14.4, Bürkner, 2017) to fit the Bayesian mixed model. The *brms* package is based on the probabilistic programming language Stan, which uses a Markov-Chain-Monte-Carlo sampling. This sampling method derives parameter estimates from a multidimensional parameter space whose number of dimensions is determined by the number of parameters. Estimates are produced by an iterative algorithm which can be executed multiple times (i.e., by multiple *chains*), and where distributions of estimates should be similar over different iterations and different chains. This can be assessed using chain plots where parameter distributions are depicted between chains and over iterations (McElreath, 2020). In addition, differences between chains can be assessed by the $\hat{R}$ value which should be lower than 1.01 (Vehtari et al., 2021). We used 6 chains (Vehtari et al., 2021, recommends at least 4 chains) and 4000 iterations (of these, 2000 were warmup iterations). These chains and iterations should result in an effective sample size (valid number of values to determine parameter estimates) of at least 1000 to obtain reliable parameter estimates (Bürkner, 2017). We obtained an $\hat{R}$ value of 1.003, the lowest effective sample size was 3082, and chain plots looked well-mixed and stationary. This indicates that the model fully converged and that parameter estimates were reliable.

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Table S1*Scales and Items*

Scale	Items
Long Term Stressors	Debt or financial problems In search of an apartment, moving, or building a house Performance pressure or general problems at work Expectations or demands of family, friends, or your partner Health issues Own expectations or demands.
Positive Mood	Active Alert Inspired Determined Attentive
Negative Mood	Afraid Ashamed Hostile Upset Nervous
Everyday Work Stressors	I had to hurry to get to an appointment. I was interrupted during a task or at work. I had to do something that I did not really know how to do. I was criticized or insulted. I was treated in an unfriendly manner by a colleague/supervisor/customer. I did not understand a task. I had a conflict with a colleague/supervisor/customer. I had to work longer than intended. I could not complete everything that I had planned to complete. I was exposed to an unpleasant situation (e.g., a presentation, an accident) I was not satisfied with my performance today. I was at work although I was sick. Someone did not fulfill an agreement. I received bad news. I was competing with someone else. I stayed late at work.

Supplemental File for Review 2**brms Code**

The following code was used in the multilevel, multivariate Bayes analysis using the package brms in R.

Notes on abbreviations: pm: person-mean centered version of this variable; pmc: grand-mean centered person mean of this variable.

```
fit0 <- brms::brm(  
  data = tmp,  
  family = gaussian(),  
  formula = brms::bf(mvbind(  
    fundamental_frequency,  
    intensity,  
    speechrate,  
    jitter,  
    shimmer  
  ) ~ 0 +  
    sex +  
    age_pm_z +  
    longtermstressors_pm_z +  
    sun_vs_work +  
    positive_mood_pm_z +  
    positive_mood_pmc_z +  
    negative_mood_pm_z +  
    negative_mood_pmc_z +  
    everydaystressors_pm_z +  
    everydaystressors_pmc_z +
```

```

perceived_stress_pm_z +
perceived_stress_pmc_z +
everyday_working_hours_pm_z +
everyday_working_hours_pmc_z +
everydaystressors_pmc_z:perceived_stress_pmc_z +
everydaystressors_pm_z:perceived_stress_pm_z +
(1 | p | code)) +
brms::set_rescor(FALSE),
prior = c(
brms::set_prior("normal(0, 3)", class = "b", resp = "fundamental_frequency"),
brms::set_prior("normal(150, 100)", class = "b", coef = "sexfemale", resp =
"fundamental_frequency"),
brms::set_prior("normal(150, 100)", class = "b", coef = "sexmale", resp =
"fundamental_frequency"),

brms::set_prior("normal(0, 3)", class = "b", resp = "intensity"),
brms::set_prior("normal(60, 5)", class = "b", coef = "sexfemale", resp = "intensity"),
brms::set_prior("normal(60, 5)", class = "b", coef = "sexmale", resp = "intensity"),

brms::set_prior("normal(0, 3)", class = "b", resp = "speechrate"),
brms::set_prior("normal(3, 1)", class = "b", coef = "sexfemale", resp = "speechrate"),
brms::set_prior("normal(3, 1)", class = "b", coef = "sexmale", resp = "speechrate"),

brms::set_prior("normal(0, 3)", class = "b", resp = "jitter"),
brms::set_prior("normal(2.8, 1)", class = "b", coef = "sexfemale", resp = "jitter"),
brms::set_prior("normal(2.8, 1)", class = "b", coef = "sexmale", resp = "jitter"),

brms::set_prior("normal(0, 3)", class = "b", resp = "shimmer"),
brms::set_prior("normal(10, 3)", class = "b", coef = "sexfemale", resp = "shimmer"),

```

```
brms::set_prior("normal(10, 3)", class = "b", coef = "sexmale", resp = "shimmer"),

brms::set_prior("student_t(10, 0, 10)", class = "sd", resp = "fundamental_frequency"),
brms::set_prior("student_t(10, 0, 10)", class = "sd", resp = "intensity"),
brms::set_prior("student_t(10, 0, 10)", class = "sd", resp = "speechrate"),
brms::set_prior("student_t(10, 0, 10)", class = "sd", resp = "jitter"),
brms::set_prior("student_t(10, 0, 10)", class = "sd", resp = "shimmer"),

brms::set_prior("lkj(3)", class = "cor")
),
sample_prior = TRUE,
save_model = "./main_cache/fit0.stan",
file = "./main_cache/fit0",
refresh = if (interactive()) 200 else 0,
chains = meta$brms_chains,
iter = meta$brms_iterations,
seed = meta$seed,
control = list(adapt_delta = .99)
)
fit0 <- brms::add_criterion(fit0, "bayes_R2", file = "./main_cache/fit0")
```