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Acoustic Speech Features in Parkinson's Disease: The Role of Dopamine

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Abstract

Introduction: Parkinson's disease (PD) is a neurodegenerative disorder associated with motor and cognitive impairments, including speech impairments. Although dopaminergic medication is widely used to alleviate motor impairments, the effects on acoustic speech features remain unclear. This study investigates whether acoustic speech features can predict ON/OFF medication states in patients with PD.

Methods: Forty-five Dutch-speaking patients with PD participated in two semi-structured interviews of 15 minutes each, with the first interview conducted in the OFF-medication state and the second interview after dopaminergic medication intake in the ON-medication state. Acoustic speech features (pitch, loudness, and jitter) were extracted using OpenSMILE. A Generalized Linear Mixed Model (GLMM) and a Generalized Estimating Equation (GEE) were performed to evaluate the predictive value of these predictors. Due to estimation instabilities of model predictors in the GLMM, indicated by a non-positive definite Hessian matrix, the GEE was used as the primary model.

Results: The results showed that pitch, loudness, and jitter had limited predictive value for distinguishing between ON/OFF medication states. Although pitch was a statistically significant predictor, the effect size was small, indicating limited practical significance.

Conclusion: These findings suggest that the investigated acoustic speech features alone are insufficient for predicting ON/OFF medication states in patients with PD. Future research may focus on combining (acoustic) speech features with other biomarkers to improve prediction accuracy.

Keywords: Parkinson's disease, dopaminergic medication, acoustic speech features, ON/OFF medication states

Acoustic Speech Features in Parkinson's Disease: The Role of Dopamine

Parkinson's disease (PD) is a progressive neurodegenerative disorder characterized by the degeneration of dopaminergic neurons in the substantia nigra, leading to dopamine deficiency (Khaskhoussy & Ben Ayed, 2023; Veetil et al., 2023). PD is also the second most common neurodegenerative disorder after Alzheimer's disease, with a higher prevalence in men and increasing incidence with advancing age (Khaskhoussy & Ben Ayed, 2023). Core symptoms of PD are motor-related and include rigidity, slowness of movement (bradykinesia), resting tremors, and postural difficulties. In addition to these core motor symptoms, patients with PD may exhibit non-motor symptoms, including cognitive impairments, sleep disturbances, and sensory disturbances (Veetil et al., 2023). One of the earliest changes in people with PD, however, is speech impairment (Veetil et al., 2023). Up to 90% of patients with PD experience some type of speech impairment (New et al., 2015). Specifically, regarding acoustic speech features, which represent the physical properties of spoken language, patients with PD exhibit increased jitter, a high amount of voice disturbances, and reduced pitch variability (Gamboa et al., 1997).

To compensate for dopamine deficiency and to alleviate motor symptoms, dopaminergic medications such as Levodopa have been used for decades. However, the relationship between dopaminergic medication and speech remains unclear (Tykalova et al., 2022). Currently, the diagnosis of PD is primarily based on the presence of core motor symptoms, which appear relatively late in the disease course. Due to the slow progression of PD (with an estimated latency of approximately 13 years between the premotor and motor stages), increasing life expectancy, and the fluctuating nature of symptoms, there is a need for objective and non-invasive markers of functional changes, such as acoustic speech features (Amoroso et al., 2018). Therefore, the present study investigates the extent to which acoustic speech features can predict ON/OFF medication states in patients with PD.

Acoustic speech features provide insight into speech characteristics that are affected by motor speech impairments. Motor speech impairments in PD are most often clinically characterized as hypokinetic dysarthria, marked by articulatory, prosodic, acoustic, and phonatory impairments of speech (Coy & Whitfield, 2024; Knowles et al., 2018). Typical manifestations of hypokinetic dysarthria include reduced overall loudness, reduced utterance length, monopitch, monoloudness, altered speech rate, and altered articulation (Coy & Whitfield, 2024; Pérez-Toro et al., 2022). Subjective reports reveal that speech worsens when speaking for a longer amount of time (Smith et al., 2025). These motor speech impairments in hypokinetic dysarthria are associated with dopamine deficiency in the substantia nigra (Khaskhoussy & Ben Ayed, 2023). While hypokinetic dysarthria is the most common speech disorder in PD, other speech impairments, such as apraxia of speech (characterized by impairments in speech motor planning and programming), have also been reported (Presotto et al., 2015). Although these disorders differ in their underlying mechanisms, both involve disruption in the coordination of multiple sensorimotor processes required for efficient speech production. Furthermore, speech production is not only influenced by motor processes but also by linguistic and cognitive factors (Rohl et al., 2022). Together, these findings highlight the complex, multifaceted nature of speech impairment in PD.

To objectively quantify speech in patients with PD, researchers commonly analyze acoustic speech features. Studies have shown that patients with PD exhibit reduced pitch variability (monopitch), increased speech perturbations (higher jitter and shimmer), reduced phonation range, and reduced loudness compared to healthy controls. (Coy & Whitfield, 2024; Gamboa et al., 1997; Holmes et al., 2000). However, findings regarding mean fundamental frequency (pitch) are inconsistent across studies. Furthermore, previous research has emphasized the importance of dynamic acoustic speech features in differentiating patients with PD from healthy controls (Proença et al., 2013). Taken together, previous studies have

investigated a broad range of acoustic speech features in PD, including measures of pitch (variability), speech perturbations, loudness, and phonation range. However, it remains unclear which of these acoustic speech features are most clinically relevant for distinguishing between ON/OFF medication states.

Dopaminergic medication, especially levodopa (a dopamine precursor), has been used for decades as pharmacotherapy to replenish dopamine deficiency and therefore reduce motor symptoms in PD. The effects of dopaminergic medication on speech, however, are mixed and poorly understood (Tykalova et al., 2022). In a study comparing patients with PD between the OFF-medication state, defined as the period following at least 12 hours of overnight withdrawal from dopaminergic medication, and the ON-medication state, defined as the period 60-90 minutes after intake of dopaminergic medication, no significant effect of dopaminergic medication on acoustic speech features was found (Mračková et al., 2023). However, these results may be attributed to the short time interval between medication withdrawal and speech assessment, which may not have allowed the effects of dopaminergic medication to wear off. Another study emphasized that the effect of dopaminergic medication on acoustic speech features is limited, except for an increase in sustained phonation during the ON-medication state of female patients with PD (Cavallieri et al., 2021). In contrast to these findings, another study reported an association between dopaminergic medication and increased overall loudness and speech rate (Ho et al., 2008). The impact of these changes, either positive or negative, on speech may depend on the speech patterns of the individual (Ho et al., 2008). Lastly, patients with PD in the ON-medication state showed increased pitch variability compared to patients in the OFF-medication state (Thies et al., 2024).

This Study

Previous studies generally reported a limited and non-significant relationship between dopaminergic medication and acoustic speech features in patients with PD. However, these

findings should be interpreted with caution, as methodological limitations complicated several studies. For example, studies included small sample sizes, focused predominantly on male participants, included mainly patients with advanced PD, or were conducted in non-Dutch-speaking countries (Cavallieri et al., 2021; Mračková et al., 2023). Consequently, it remains unclear whether acoustic speech features can reliably distinguish ON/OFF medication states across different populations.

The main objective of this study is articulated through the following two research questions: (1) “Can acoustic speech features predict ON/OFF medication states in patients with Parkinson's disease? (2) “Which acoustic speech features are the strongest predictors of ON/OFF medication states in patients with Parkinson's disease?”

Based on the existing literature, it was hypothesized that acoustic speech features would have limited predictive value for distinguishing between ON/OFF medication states in patients with PD. However, loudness was hypothesized to be the only significant and strongest predictor of ON/OFF medication states.

Methods

Participants

This study used a subset of participants from the PRAAT study, as no new participants were recruited (UMC Utrecht, 2017). The PRAAT study was a research project that collected audio recordings of conversations with patients with depression, Alzheimer’s disease, and PD. The aim of the PRAAT study was to investigate whether speech features derived from audio recordings could be used as objective markers of disease-related changes in these conditions. For the PD dataset, a priori power analysis was not conducted. The initial sample consisted of 56 participants. However, 11 participants were excluded from the initial sample due to missing data. Therefore, the final sample comprised of 45 participants (29 males, mean age = 63; 16 females, mean age = 60). All participants were diagnosed with Parkinson's disease

(PD), were aged 18 years or older, had been treated with dopaminergic medication for at least one year, and were native Dutch speakers. Participants with uncorrected hearing disorders and speech impediments were excluded. All participants provided written informed consent before participation. To minimize attention to speech and language, participants were informed that the interview would be used to analyze the content of the conversations. During the debriefing, participants were informed that speech, rather than content, was analyzed. Upon completion of participation, an incentive of a 10-euro gift card was provided. Ethical approval was obtained from the UMC Utrecht Ethics Review Committee.

Interview Procedure

Trained physicians conducted two semi-structured interviews with each participant. First, a 15-minute semi-structured interview was conducted with PD patients in the absence of dopaminergic medication (OFF-medication state). After the first interview, participants were instructed to take dopaminergic medication (ON-medication state) and wait in the waiting room for 60-90 minutes. Following the onset of the effects of the dopaminergic medication, the second 15-minute interview was conducted. The physicians intervened as little as possible while ensuring the conversation remained natural and comfortable to elicit spontaneous speech. The questions used in the interviews were randomly selected by the physician from a list of questions from the PRAAT study (UMC Utrecht, 2017; Appendix A). All questions were neutral and posed no harm to the participants. However, if participants did not want to discuss a question, the question was skipped. Data were collected using a TASCAM DR-40 recording device and AKG-CG-C5441 cardioid microphones. Speech was recorded via two channels, one for the physician and one for the participant, with a sampling frequency of 16,000 Hz.

Data preprocessing

Two audio recordings (ON/OFF medication states) were obtained from each participant. All recordings were checked for quality, crosstalk, and completeness using PRAAT software (Boersma et al., 1992). These quality checks were not performed blinded to the participants' ON/OFF medication states.

Acoustic speech features were extracted by the PRAAT research group from the first 240 seconds of each recording using the OpenSMILE toolkit (Eyben et al., 2010). OpenSMILE analyzes speech by dividing audio recordings into short frames and computing acoustic speech features for each frame (Eyben et al., 2010). These frame-level features were then aggregated using statistical functionals, resulting in a single value for each acoustic speech feature per participant per recording.

Acoustic Speech Features

A hypothesis-driven method was used for acoustic speech feature selection. The following acoustic speech features were selected: pitch, loudness, and jitter (Table 1). Loudness and jitter were computed acoustic speech features. This means that values are relative, meaning that values should be interpreted in relation to other observations within the dataset rather than using the values as absolute measures.

Table 1

Acoustic speech features and definitions

Acoustic speech features	Definition
Pitch	Logarithmic F0 on a semitone frequency scale, starting at 27.5 Hz (semitone 0). Arithmetic mean.
Loudness	Estimate of perceived signal intensity from an auditory spectrum.
Jitter	Deviations in individual consecutive F0 period lengths.

Dopaminergic Mediation

Speech recordings were obtained under two conditions: OFF-medication and ON-medication. The OFF-medication state was operationally defined as the period following at least 12 hours of overnight withdrawal from dopaminergic medication. The ON-medication state was operationally defined as the period 60-90 minutes after intake of dopaminergic medication. The exact medication profiles were not systematically recorded, as dopaminergic medication is highly individualized and typically consists of combinations of multiple medications. Therefore, medication status was defined solely by the ON/OFF medication states.

Statistical Analyses

Statistical analyses were performed using IBM SPSS Statistics (version 28; IBM CORP, 2021). To examine whether acoustic speech features could predict ON/OFF medication states and to identify the strongest predictor, a generalized linear mixed model (GLMM) was initially used. A GLMM was used to model the ON/OFF medication states while accounting for repeated measures within participants. The model assumed a binomial distribution with a logit link function. ON/OFF medication states were defined as the binary dependent variable. The acoustic speech features pitch, loudness, and jitter were included as fixed effects, and a random intercept for participants was included to account for within-subject variability. However, the GLMM showed estimation instability in the dataset, indicated by a non-positive definite Hessian matrix. Therefore, model estimates were considered unreliable.

Consequently, a Generalized Estimating Equation (GEE) was performed as a more robust alternative. The GEE was used to examine whether acoustic speech features predicted ON/OFF medication states at the population-averaged level, whereas the GLMM estimated subject-specific effects. The GEE also assumed a binomial distribution with a logit link

function. ON/OFF medication states were again defined as the binary dependent variable, and the acoustic speech features were included as predictors. Participant ID was included as the clustering variable to account for repeated measures within participants. The convergence criteria were set to 1e-6, and the working correlation matrix structure to exchangeable.

Results

Model Assumptions

Model assumptions relevant to both GLMM and GEE were assessed before model interpretation. Measurements between participants were assumed to be independent, while observations within participants were expected to be correlated and were accounted for by the GLMM and GEE. No evidence of multicollinearity was found (pitch: *VIF* = 1.456; loudness: *VIF* = 1.067; jitter: *VIF* = 1.537). Thus, no violations of the assessed model assumptions were identified.

Descriptive Statistics

Descriptive statistics for the acoustic speech features are presented in Table 2. The means and standard deviations were calculated for each acoustic speech feature.

Table 2

Descriptive Statistics

	N	M	SD
Pitch	90	26.47	3.84
Loudness	90	0.16	0.15
Jitter	90	0.05	0.02

Main Analyses

To address the research questions of whether acoustic speech features can predict ON/OFF medication states in patients with PD and which acoustic speech features are the strongest predictors of ON/OFF medication states, the main results of the GLMM and GEE

are presented. The GLMM showed a non-positive definite Hessian matrix, indicating estimation instabilities. This suggests that the results of the GLMM should be interpreted with caution. The GLMM showed a low pseudo-R-squared ($R^2 = 0.020$). This shows the limited explanatory power of the model. The acoustic speech features (pitch, loudness, and jitter) predicted only 2% of the variance in ON/OFF medication states. However, none of the individual acoustic speech features made a significant contribution to predicting ON/OFF medication states (pitch: B = -0.08, p = 0.224; loudness: B = -0.34, p = 0.822; jitter: B = -4.71, p = 0.713) (Table 3, Appendix B). The model had a classification accuracy of 55.6% (62.2% correct classification for OFF-medication; 48.8% correct classification for ON-medication) (Table 4, Appendix B). This means that the model was limited in distinguishing between ON/OFF medication states based on the acoustic speech features.

Due to the instabilities of the GLMM estimations, as indicated by a non-positive definite Hessian matrix, a GEE was performed as an alternative analysis. The GEE showed that only pitch was a statistically significant predictor of ON/OFF medication states (Wald $\chi^2 = 7.40$, B = 4.56E-6, p = 0.007) (Table 5, Appendix C). A positive coefficient indicated that a higher pitch was associated with higher odds of being in the ON-medication state. However, the practical significance of this effect was limited due to a small regression coefficient. Loudness (Wald $\chi^2 = 0.34$, B = 1.74E-5, p = 0.560) and jitter (Wald $\chi^2 = 0.40$, B = 0.00, p = 0.527) were not significant predictors of ON/OFF medication states (Table 5, Appendix C).

Discussion

Summary of Findings

The present study examined whether acoustic speech features could predict ON/OFF medication states in patients with PD and sought to identify which acoustic speech feature, if any, was the strongest predictor of ON/OFF medication states. The results of the Generalized Linear Mixed Model (GLMM) should be interpreted with caution due to the non-positive

definite Hessian matrix, indicating estimation instability. Consequently, the classification accuracy (55.6%) and predictor estimates from the GLMM were not considered reliable. Therefore, the Generalized Estimating Equations (GEE) were used as the primary model for interpreting the study findings. Overall, the findings indicated that pitch, loudness, and jitter had limited predictive value for distinguishing between ON/OFF medication states. Although pitch emerged as a statistically significant predictor in the GEE, the effect size was small, suggesting limited practical significance. Thus, our findings indicate that acoustic speech features may have limited utility for predicting ON/OFF medication states in patients with PD.

Interpretation of Findings

The limited predictive value of acoustic speech features suggests that acoustic speech impairments in PD are likely influenced by factors beyond dopaminergic deficiency alone. Although dopaminergic medication is used to alleviate motor symptoms, the effect on acoustic speech features appears to be limited. This interpretation is consistent with previous studies, which also report no significant associations between jitter and ON/OFF medication states (Cavallieri et al., 2021; Mračková et al., 2023). However, in contrast to Ho et al. (2008), who found loudness to be a significant predictor of ON/OFF medication states, the present study found no significant association between loudness and ON/OFF medication states. Although pitch appeared to be a statistically significant predictor, the effect size was small, suggesting that pitch has no practical significance.

One possible explanation for these findings is that speech is a multidimensional process rather than purely a motor function. Speech involves the interaction of higher-order cognitive processes, such as working memory, goal-directed behavior, and integration of multiple sensory inputs, with lower-order motor processes (Altmann & Troche, 2011; Rohl et al., 2022). As PD affects both higher-order cognitive processes and lower-order motor

processes, higher-order cognitive processes may remain relatively unaffected by dopaminergic medication, thereby limiting improvements in acoustic speech. Moreover, speech production relies on auditory and kinesthetic feedback loops (Altmann & Troche, 2011; Rohl et al., 2022). Alterations in these feedback loops may contribute to the limited predictive value of acoustic speech features, despite the use of dopaminergic medication. Lastly, PD is increasingly recognized as a multifactorial neurodegenerative disorder. Beyond dopamine deficiency, alterations in serotonin and noradrenaline may also contribute to speech impairment. (Ye, 2022). This means that acoustic speech features may reflect dysfunctions across multiple neurotransmitters, which could explain the limited responsiveness to dopaminergic medication.

Strengths

The present study offers several methodological strengths that support the relevance of the research findings. First, the use of semi-structured interviews may have enhanced the ecological validity of the study. Participants were encouraged to speak freely with the interviewer and were informed that the researcher would focus on the content of the interview rather than on speech. This approach likely reduced the participants' awareness of their own speech production, thereby encouraging participants to produce speech that more closely resembles natural, everyday conversation. Consequently, the collected speech data may provide a more realistic representation of everyday speech in patients with PD, which may strengthen the generalizability of the findings. This is particularly relevant when comparing the present methodology with that used by Mračková et al. (2023), who used a standardized reading task in which speech production was highly controlled. Although a standardized reading task offers experimental control, it may not fully capture the characteristics of everyday speech production in patients with PD. By using semi-structured interviews, the present study may offer greater ecological validity than standardized speech tasks.

Second, the present study was conducted in a Dutch-speaking population, whereas previous studies were conducted in non-Dutch-speaking populations. Consequently, the results of this study extend previous research findings by suggesting that the limited predictive value of acoustic speech features (pitch, loudness, and jitter) for ON/OFF medication states may also be observed in patients with PD in a Dutch-speaking population.

Third, a hypothesis-driven approach was used to select acoustic speech features, which enhances the interpretability of the research findings. As acoustic speech feature selection was theoretically grounded, an exploratory approach was avoided. This facilitates comparisons between research findings and enhances the possibility of replicating the current study.

Finally, OpenSMILE was used to objectively extract acoustic speech features (Eyben et al., 2010). All acoustic speech features were calculated using predefined algorithms to ensure consistency in data extraction across participants. Furthermore, OpenSMILE enabled the detection of subtle acoustic speech changes that may not be easily detectable by humans. Thus, the use of OpenSMILE may have reduced the risk of measurement bias.

Limitations

Despite the strengths of the study, several limitations should be considered. First, a relatively small sample size (N = 45) may have limited statistical power to detect small effects. An a priori power analysis was not conducted because existing data from the PRAAT study were used. A post hoc power analysis was not performed, as such an analysis provides limited additional information after obtaining non-significant results. Additionally, 11 participants were lost from the initial sample, which may further reduce statistical power. Given that medication-related changes in acoustic speech features are generally small, larger samples may be required to reliably detect associations between acoustic speech features and ON/OFF medication states.

Second, only three acoustic speech features (pitch, loudness, and jitter) were included in the analyses. Additional acoustic speech features, such as shimmer and bandwidth, could be incorporated into future GLMM and GEE to improve predictive performance. However, the multidimensional nature of speech extends beyond acoustic speech and also involves speech features such as semantics and syntax (Altmann & Troche, 2011). Features such as speech rate, autocorrelation, and entropy could be added to the GLMM and GEE. Incorporating additional acoustic speech features and non-acoustic speech features may provide a more comprehensive representation of speech changes associated with ON/OFF medication states.

Third, the study did not account for disease-related characteristics that may influence speech production. Variables such as cognitive functioning, fatigue, and PD severity may affect performance during speech assessment.

Finally, GLMM estimates could not be considered reliable due to a non-positive definite Hessian matrix. Hence, estimates of the explained variance, classification accuracy, and p-values should be interpreted with caution. A non-positive definite Hessian matrix may be related to low sample size, limited number of predictors, or insufficient number of repeated measures. This may have led to an overly complex model. Due to these limitations, a GEE was performed as an alternative analysis. However, unlike a GLMM, the GEE did not compute the classification accuracy for predicting ON/OFF medication states. Consequently, the GEE provided less direct evidence regarding the predictive value of acoustic speech features to distinguish between ON/OFF medication states.

Practical Implications

The findings of the present study have several practical implications. The limited predictive value of acoustic speech features (loudness, pitch, jitter) suggests that using acoustic speech features alone may be insufficient to objectively differentiate between

ON/OFF medication states in patients with PD. Consequently, clinicians should not solely rely on acoustic speech features to monitor changes in ON/OFF medication states or fluctuations in medication effectiveness. Nevertheless, the non-invasive, low-cost, and potentially home-based application of speech monitoring remains promising for future clinical implications. Incorporating additional linguistic measures together with machine learning techniques may improve the development of speech-based measures for predicting ON/OFF medication states in patients with PD.

Future Directions

The strengths and limitations of the present study will provide several directions for future research. Increasing sample size and implementing additional (acoustic) speech features should be a methodological priority. Although the hypothesis-driven feature selection was theoretically justified, it may not fully capture the optimal predictors for ON/OFF medication states. Therefore, a LASSO regression should be considered to determine the most relevant predictors. Moreover, machine learning methods such as Random Forest analysis may provide additional insights into the relative importance of individual speech features. Future research may also focus on implementing different biomarkers alongside (acoustic) speech features, such as facial expressions and handwriting measures, to improve the prediction of ON/OFF medication states in patients with PD.

Conclusion

The results of this study showed that the investigated acoustic speech features (pitch, loudness, and jitter) had limited predictive value for distinguishing between ON/OFF medication states in patients with Parkinson's disease. Therefore, acoustic speech features alone appear insufficient for predicting ON/OFF medication states in patients with Parkinson's disease. Future research should investigate whether combining acoustic speech

features with additional speech features and other biomarkers, such as handwriting and facial expression measures, can improve the prediction of ON/OFF medication states.

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Appendix A

Interview Questions

Studienummer PRAAT:_____ Datum: ____/ ____/ _____Ingevuld door:

_____

PRAAT

Vragenlijst compleet

☐ 1 Zwemles: Kun je vertellen over je zwemles van vroeger? Hoe vond je dat?

Wat vond je het moeilijkst? En het leukst?

☐ 2 Tandarts: Kun je vertellen over je tandartservaringen (slechte en goede

ervaringen)? Kun je bijvoorbeeld vertellen over de laatste keer

dat je bent geweest? En hoe heb je dat als kind ervaren?

☐ 3 Wereld: Als je nu overal ter wereld heen mocht gaan, waar zou je

heengaan?

☐ 4 Rijbewijs: Heb je een rijbewijs? Zo ja, kun je wat vertellen over hoe de

lessen gingen en hoe het examen ging?

☐ 5 Pretpark: Ben je wel eens in een pretpark geweest? Kun je daar wat over

vertellen? Heb je een favoriet pretpark, vertel daar eens over?

Waarom is het je favoriete park?

☐ 6 Cadeau: Wat is het leukste cadeau dat je ooit hebt gekregen? Van wie

kreeg je het?

☐ 7 TV: Naar welke Nederlandstalige Tv-programma's kijk je vaak? En

aan welke heb je een hekel? Waarom?

☐ 8 Sport: Kijk je wel eens naar sport, zoals voetbalwedstrijden? Zo ja, naar

welke wedstrijden en wat vind je daarvan? En ben je een fan

van een bepaalde club of sporter?

☐ 9 Privé: Heb je liever een privévliegtuig of een privé-eiland? En waarom?

☐ 10 Gisteren: Hoe ziet een gewone dag voor jou eruit? Wat doe je van ’s ochtends tot s’ avonds? Kun je de dag van gisteren beschrijven?
Wat heb je gedaan, van opstaan tot slapen gaan?

☐ 11 Zomer: Wat is je favoriete bezigheid in de zomer? Waarom?

☐ 12 Verjaardag: Hoe vier je meestal je verjaardag? Hoe was je laatste verjaardag?

☐ 13 Huis: Wat voor soort huis is je droomhuis? Waar zou dit huis staan?
Met wie zou je er willen wonen?

☐ 14 Droom: Kun je vertellen over een droom die je hebt gehad? Kun je je laatste droom beschrijven?

☐ 15 Eigen werk: Wat voor werk doe je/heb je recent gedaan? Wat sprak je daarin aan?

☐ 16 Leeftijd: Als je voor altijd een bepaalde leeftijd kon hebben, welke leeftijd zou dat dan zijn? Waarom?

☐ 17 Favoriete eten: Wat was je favoriete eten toen je klein was?

☐ 18 Uit eten: Als je uit iedereen in de wereld kon kiezen, met wie zou je dan uit eten willen?

☐ 19 Klusje: Welk klusje in huis vind je echt vreselijk om te doen? Waarom?
Doe je het dan?

☐ 20 Feestjes: Wat was één van de beste feestjes waar je ooit bent geweest?

☐ 21 Onzichtbaar: Wat zou je doen als je een dag onzichtbaar zou kunnen zijn?

☐ 22 Sollicitatie: Hoe ervaar je sollicitatiegesprekken? Ben je vaak zenuwachtig?
Kun je wat vertellen over je laatste sollicitatiegesprek? Was je zenuwachtig? Ben je aangenomen?

☐ 23 Taal: Wat vind je een mooie taal? Zou je deze taal nog willen leren?

Zou je nog een andere taal willen leren? Waarom?

☐ 24 Jeugdherinnering: Wat is je favoriete jeugdherinnering? Wie waren erbij? Waarom vind je dat zo'n fijne herinnering?

☐ 25 Loterij: Wat zou je doen als je een miljoen zou winnen?

☐ 26 Eten: Wat is het vreemdste dat je ooit hebt gegeten? (bv. slak, oester)

☐ 27 Feestdagen: Hoe werden bij jou thuis de feestdagen gevierd?

☐ 28 Onbewoond eiland: Stel je wordt gedropt op een onbewoond eiland en moet daar een jaar blijven, welke 3 dingen zou je dan meenemen?

☐ 29 Geboren?: Waar ben je geboren? Welke stad, ziekenhuis of thuis? Wie waren daarbij?

☐ 30 Ouders: Lijk je op je ouders? Op wie lijk je het meest, waarom?

☐ 31 Broers/zussen: Heb je broers of zussen? Op wie lijk je het meest, waarom? Met wie had je het meest ruzie?

☐ 32 Soort kind: Wat voor soort kind was je toen je klein was?

☐ 33 Tijdmachine: Als je een tijdmachine had, naar welke tijd in de toekomst/verleden zou je gaan? Waarom?

☐ 34 Knuffel: Had je vroeger een lievelingsknuffel? Of iets anders dat je altijd bij je wilde hebben?

☐ 35 Wereldprobleem: Als je vandaag wereldprobleem mocht oplossen, welk probleem zou dat zijn? Waarom?

☐ 36 Huisdieren: Heb je wel eens een huisdier gehad? Zou je een huisdier willen? Wat voor een? Hoe was je band daarmee?

☐ 37 Belangrijke mensen: Welke mensen waren belangrijk voor je in je jeugd? Waarom?

☐ 38 Auto: Als je nu een auto mocht kopen, wat voor auto zou dat dan zijn?

☐ 39 Stripfiguur: Wat is je favoriete stripfiguur? Waarom die?

☐ 40 Ziek als kind: Was je weleens ziek als kind? Heb je weleens in het ziekenhuis gelegen?

☐ 41 Dier: Als je een dier was, welk dier zou je dan zijn en waarom?

☐ 42 Problemen vroeger: Haalde je vroeger wel eens kattenkwaad uit? Werden je ouders dan boos?

☐ 43 Beste vriend(in): Hoe heb je je beste vriend/in ontmoet?

☐ 44 Persoon: Als je met één persoon op aarde nu mocht spreken, met wie zou dat zijn?

☐ 45 Spellen vroeger: Wat voor spellen speelde je vroeger? Waar speelde je meestal? Buiten/binnen? Met wie?

☐ 46 Vakantie: Ga je wel eens op vakantie? Wat is je favoriete vakantiebestemming? Waarom?

☐ 47 Goed nieuws: Kun je je de laatste keer herinneren dat je goed nieuws kreeg? Wat voor nieuws was dat? Wat voor effect had dat op je?

☐ 48 Verliefd?: Ben je wel eens verliefd geweest? Weet je nog hoe jullie in gesprek kwamen? Was je verlegen? Weet je nog hoe jullie eerste afspraakje was? Was je zenuwachtig?

☐ 49 Gebeurtenis: Als je getuige zou kunnen zijn van elke gebeurtenis in het verleden, heden of toekomst, welke zou het dan zijn?

☐ 50 Belangrijk moment: Wat zijn belangrijke momenten in je leven geweest?

☐ 51 Zintuigen: Als je één van je zintuigen op moest geven welke zou het dan zijn? (horen, zien, voelen, ruiken of proeven) Waarom?

☐ 52 Werk ouders: Wat voor werk doen/deden je ouders?

☐ 53 Week: Kun je iets leuks vertellen wat je hebt meegemaakt? Wat is het beste/leukste dat je deze week is overkomen?

☐ 54 Pizza: Hoe ziet jouw perfecte pizza eruit? Wat zit er allemaal op?

☐ 55 God: Als je voor één dag God zou zijn, wat zou je dan doen?

☐ 56 Belangrijke rol: Welke mensen spelen nu een belangrijke rol in je leven? Waarom?

☐ 57 Droombaan: Wat wilde je vroeger worden (wat voor baan)? Heb je dat lang gedacht? Zou je dat nu nog willen?

☐ 58 Fictief figuur: Als je elk willekeurige fictieve persoon zou kunnen zijn, wie zou je dan kiezen?

☐ 59 Kledingstuk: Wat is het raarste kledingstuk dat je ooit hebt gedragen?

☐ 60 Boek: Wat was je favoriete boek toen je klein was? En waarom was je daar zo dol op?

1. Aantal vragen gesteld: _____

2. Welk kitje heb je gebruikt? 1 / 2 / 3 / ___

3. Tascam nummer audio bestand: _____

4. Audio bestand opgeslagen op schijf? Ja / Nee

5. Opmerking over opname:

o Geen bijzonderheden

o Wel een opmerking, namelijk:

Appendix B

Table 3

Fixed coefficients table

Model term	B	SE	t	Sig.	95% CI
Intercept	2.51	2.21	1.13	0.261	[-1.87, 6.91]
Pitch	-0.08	0.07	-1.23	0.224	[-0.22, 0.05]
Loudness	-0.34	1.51	-0.23	0.822	[-3.34, 0.82]

Jitter	-4.71	12.76	-0.37	0.713	[-30.07, 0.71]

Table 4

Classification table

		Predicted	Predicted
Observed		OFF	ON
OFF	Count	28	27
	% within observed	62.2%	37.8%
ON	Count	23	22
	% within observed	51.1%	48.8%

Note: overall percent correct = 55.6%

Appendix C

Table 5

GEE parameter estimates

Model Parameter	B	SE	Sig.	Wald χ^2	95% Wald CI
Intercept	0.00	5.22E-5	0.010	6.71	[-3.29E-5, 0.00]
Pitch	4.56E-6	1.67E-6	0.007	7.40	[1.27E-6, 7.84E-6]
Loudness	1.74E-5	2.98E-5	0.560	0.34	[-4,11E-5, 7.59E-6]
Jitter	0.00	0.00	0.527	0.40	[-0.00, 0.00]

Acknowledgements

Use of IA

No content generated by AI technologies has been presented as my own work. ChatGPT (version 5.5) was solely used as a supporting tool for literature exploration and to provide suggestions for refining self-written texts.