VOICE-BASED PREDICTION OF DROWSINESS FOR ENHANCING AUTOMOTIVE SAFETY FEATURES

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ABSTRACT: This study proposes a novel, non-invasive method for predicting drowsiness based on short voice recordings, targeting applications in automotive safety and industrial risk management. Drowsiness remains a critical factor in traffic and workplace accidents, particularly in sectors where continuous alertness is vital. To address this issue, we developed a model that estimates the probability of heart rate decreases—a physiological marker associated with drowsiness—by extracting Mel-frequency cepstral coefficients (MFCCs) from speech and applying logistic regression analysis. Systematic data augmentation techniques were employed to enhance model generalization without requiring large-scale datasets. The proposed model achieved an Area Under the Curve (AUC) of 0.649 and an overall accuracy of 62.1%, demonstrating the feasibility of using voice as a proxy for physiological monitoring. Compared to conventional methods relying on EEG or HRV signals, our voice-only framework offers a passive, scalable, and practical solution for early-stage drowsiness detection. Future research will focus on incorporating prosodic and spectral-temporal features, adopting deep learning architectures, and integrating multimodal IoT-based sensing to improve robustness and real-world applicability.

KEYWORDS: *Drowsiness Detection; Voice-based Monitoring; Heart Rate Prediction; Logistic Regression; MFCC Features; Passive Sensing*

1.0 INTRODUCTION

Drowsiness is a critical factor contributing to traffic accidents and industrial incidents, including those in the automotive sector, often resulting in serious injuries and fatalities worldwide. Numerous studies have demonstrated that early detection and mitigation of drowsiness can significantly improve safety outcomes [1,2]. Traditionally, physiological signals such as heart rate variability (HRV) and electroencephalography (EEG) have been employed to detect drowsiness [3-6]. Similarly, other physiological indicators, such as grip force, have been investigated to assess physical fatigue and performance in occupational settings [4]. However, these methods typically require specialized equipment, continuous sensor attachment, and complex processing, limiting their practicality for real-world or large-scale deployment.

Recent advancements in voice analysis and non-invasive sensing technologies have opened promising avenues for monitoring physiological and cognitive states through speech [2,3,5]. Changes in vocal characteristics—such as spectral properties and prosodic patterns—have been linked to cognitive fatigue, stress, and modulation of the autonomic nervous system [3,6-9]. Voice-based monitoring offers a passive, unobtrusive, and scalable alternative to conventional bio signal measurements, making it particularly suitable for real-time drowsiness detection in industrial and automotive applications [2,7,10].

In this study, we propose a novel approach to predict drowsiness by estimating decreases in heart rate using acoustic features extracted from voice recordings. Given the physiological association between parasympathetic dominance and heart rate reduction during drowsiness [3,6], capturing these signals through speech may enable early intervention without requiring direct physical sensors. Our framework integrates logistic regression with systematic audio processing and data augmentation, aiming to provide a lightweight, deployable solution for operational environments.

Furthermore, we benchmark our model's performance against existing HRV-based detection methods [5,6] and CNN-based facial landmark recognition approaches [9,11-14], emphasizing the comparative strengths and limitations of voice-based detection. We also discuss future directions, including the integration of deep learning models [2,11], multimodal sensing [8,15,16], and IoT-enabled real-time monitoring systems [10,13], to enhance robustness and practical deployment.

2.0 RELATED WORK

Various approaches have been proposed for drowsiness detection, primarily leveraging physiological, behavioural, and multimodal indicators. Among physiological methods, heart rate variability (HRV) and electroencephalography (EEG) have demonstrated strong associations with drowsiness episodes [5,6]. While EEG-based systems offer high classification accuracy [14], their reliance on specialized equipment and invasive sensor placement limits their practicality for daily or large-scale application.

HRV-based methods provide a more practical alternative. Several studies have shown that decreases in HRV, especially in low-frequency power, reflect increased parasympathetic activity associated with drowsiness [3,5,7]. Vicente et al. [5] confirmed the effectiveness of HRV-derived features in detecting driver drowsiness, highlighting their non-invasiveness and suitability for real-world use.

Behavioural approaches, particularly those based on facial expressions and eye movements, have also gained prominence. CNN-based facial landmark detection has shown promise in recognizing drowsiness-related cues [9,14]. Albasrawi et al. [9] and Chand et al. [8] employed CNN-based models to detect drowsiness from visual features such as eyelid closure, yawning, and head pose estimation, achieving moderate to high classification accuracy under controlled conditions. Additionally, CNN-based emotion analysis has also been explored for drowsiness detection [8].

Voice analysis has recently emerged as a non-invasive modality for monitoring physiological and cognitive states. Changes in speech characteristics—such as prosody, spectral features, and rhythm—have been linked to cognitive fatigue and autonomic regulation [3,6,9]. Ramzan et al. [2] reviewed multimodal frameworks combining vocal, visual, and physiological cues, emphasizing the potential of voice-based monitoring when integrated with machine learning.

IoT-enabled and wearable technologies have further advanced the field. Phan et al. [11,16] developed deep learning-based IoT systems for real-time fatigue detection, while Kim et al. [13] proposed lightweight architectures for wearable drowsiness monitoring. These technologies enable scalable, continuous assessment of driver state with minimal user burden.

Hybrid sensing systems, integrating behavioural and physiological signals, have also been proposed to enhance robustness [8]. These frameworks leverage the complementary strengths of different modalities to improve sensitivity and specificity under real-world conditions.

In summary, although physiological and behavioural approaches remain foundational in drowsiness detection, voice-based sensing represents a promising and emerging direction. Its unobtrusiveness and scalability make it particularly well-suited for integration into modern vehicle and industrial monitoring systems when combined with advanced machine learning algorithms and real-time data processing.

3.0 METHODOLOGY

This study introduces a novel framework for predicting driver drowsiness through passive voice analysis, offering a non-intrusive alternative to traditional physiological monitoring.

Unlike conventional approaches that rely on invasive bio signal acquisition (e.g., EEG, HRV monitors) [5,6,7], our method utilizes acoustic features extracted from brief speech recordings to infer future decreases in heart rate—an established physiological marker of drowsiness [3,5].

The overall workflow of the proposed methodology is illustrated in Figure 1. Voice recordings are collected from participants and processed to extract acoustic features, such as Mel-frequency cepstral coefficients (MFCCs). These features are input into a machine learning model to predict the probability of a future decrease in heart rate.

Since heart rate reduction is physiologically associated with parasympathetic nervous system dominance, this predicted probability serves as an indirect indicator of the likelihood of drowsiness.

Thus, our system enables passive estimation of drowsiness risk based solely on short-duration voice data, without requiring direct physiological sensing.

This prediction flow — from voice features to physiological state inference to drowsiness risk estimation — represents a technically critical innovation toward scalable and unobtrusive drowsiness detection.

The proposed framework integrates three key contributions:

- **Forward-shifted labelling:** Drowsiness is predicted by aligning voice features with heart rate reductions occurring two hours later.

- **Systematic audio data augmentation:** Pitch shifting, reverberation simulation, and noise injection are employed to increase robustness without requiring extensive data collection [2,5,8].

- **Voice-only, minimally invasive monitoring:** Designed for real-world, scalable applications where sensor-based methods are impractical.

These contributions distinguish the proposed methodology from previous work and support its deployment in automotive and industrial monitoring environments.

3.1 Collection and Specification

Heart rate data were collected from 16 participants using a wearable device (Fitbit Inspire2). Continuous heart rate measurements (in bpm) produced approximately 3 million records. Simultaneously, voice recordings were obtained via a mobile web app, captured roughly once per hour. Each audio file was stored in WAV format at 16 kHz, yielding over 1,000 recordings with an average duration of three seconds.

After cleansing (e.g., removal of corrupted and low-amplitude files), 1,000 audio samples from 12 participants were retained. These data formed the foundation for downstream processing. The dual collection of voice and heart rate data reflects a scalable, minimally invasive monitoring strategy consistent with prior studies [5,8,12,16,17].

3.2 Processing

To construct a binary classification dataset, the following preprocessing pipeline was implemented:

Step 1: Heart Rate Labelling
Chronologically ordered heart rate records were processed per participant. Mean and standard deviation were calculated, and any record falling more than one SD below the mean was labelled as 1 (indicating reduced arousal), while the rest were labelled as 0. This threshold-based strategy reflects parasympathetic activation during drowsiness [3,5].

Step 2: Voice Feature Extraction
Mel-frequency cepstral coefficients (MFCCs) were extracted from each utterance, generating 12-dimensional vectors. These features capture critical spectral information while minimizing pitch variability across speakers [2,5].

Step 3: Dataset Integration and Forward Shifting
Voice features and heart rate labels were merged by participant ID and timestamp. To simulate early detection, heart rate labels were shifted two hours forward. The resulting dataset contained 233,800 records, each comprising 12 MFCC features and a binary label.

3.3 Data Augmentation

Given the limited voice dataset, augmentation techniques were used to expand its size and diversity. The process is illustrated in Figure 2 and included:

- Pitch shifting to simulate voice variation,
- Onset jitter to introduce timing variability,
- Reverberation to mimic acoustic environments,
- White noise injection for background realism.

These transformations aimed to improve generalizability by exposing the model to varied acoustic conditions [2,5,8].

3.4 Final Dataset and Target

The final dataset consisted of 233,800 records, with 2,240 labelled as heart rate decreases—roughly 1% positive class. This class imbalance was addressed in model evaluation by prioritizing AUC over raw accuracy [9].

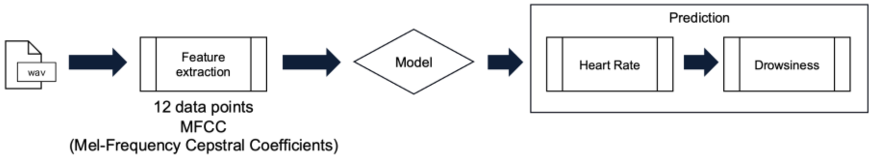

Figure 1: A flow chart of the feature selection heuristic

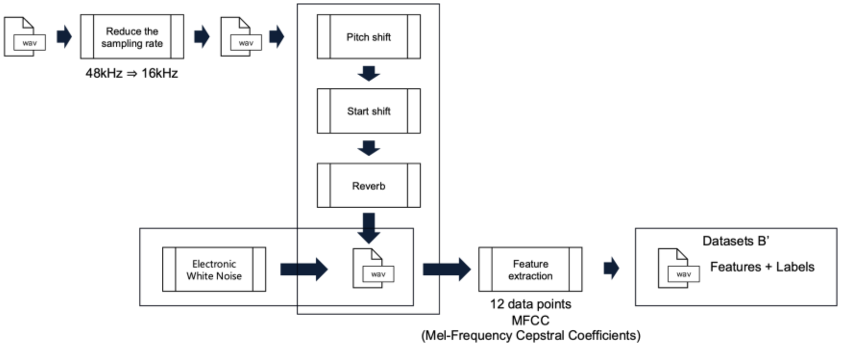

Figure 2: Procedure for Data Augmentation

4.0 MODEL ARCHITECTURE

To model the probability of physiological decline indicative of drowsiness, we employed a binary logistic regression model [13]. Logistic regression is a type of generalized linear model (GLM) that is particularly well-suited for binary classification tasks, as it estimates the probability of a binary outcome based on a linear combination of input features. This interpretable framework not only enables binary prediction but also provides a confidence level for each prediction, which is critical in safety-critical applications [10,13].

The overall model architecture and its position within the drowsiness prediction framework are illustrated in Figure 1.

In our formulation, the independent variables are the 12-dimensional MFCC feature vectors derived from voice data (Dataset B), and the dependent variable is a binary outcome from Dataset A indicating whether a heart rate decrease occurred. The model structure is mathematically represented by Equation (1):

$$logit\big(p(y=1|X)\big) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{1}$$

where β denotes the model coefficients and X represents the input feature vector. The predicted probability of a heart rate decrease is calculated by applying the logistic function, as shown in Equation (2):

$$p(y=1|X) = 1/\left(1+e^{-logit(p(y=1|X))}\right) \tag{2}$$

For classification purposes, a threshold of 0.01 is typically applied to the predicted probabilities. If $p \geq 0.01$, the model predicts a decrease in heart rate; otherwise, it predicts no decrease. This lower threshold was chosen due to the extreme class imbalance in the dataset, where heart rate decreases accounts for only approximately 1% of observations. Using a standard threshold of 0.5 would severely under detect the positive class. The adjusted threshold helps increase sensitivity (recall) for rare but critical events, such as early signs of drowsiness.

This approach offers several advantages:

- **Interpretability:**
  The contribution of each acoustic feature to the final decision can be easily interpreted based on the sign and magnitude of its corresponding coefficient [13].

- **Efficiency:**
  Logistic regression models are computationally efficient, making them suitable for real-time deployment in low-power or embedded systems.

- **Benchmarking:**
  Logistic regression provides a strong baseline against which more sophisticated models, such as deep learning architectures, can later be evaluated [13].

5.0 RESULTS

This section presents the results of the logistic regression model for predicting heart rate decreases from voice data. We analyze the contribution of individual acoustic features, evaluate the model's discriminative power, and discuss its practical implications.

5.1 Coefficients

The estimated coefficients of the logistic regression model are presented in Table 1. The independent variables were 12-dimensional

Mel-Frequency Cepstral Coefficients (MFCCs), and the dependent variable was a binary indicator of heart rate decrease.

All coefficients were statistically significant at the 5% level, confirming that each acoustic feature had a measurable effect on the prediction. Among them, mfcc_3, mfcc_2, and mfcc_4 showed positive coefficients, indicating that increases in these features were associated with a higher probability of a heart rate decrease. In contrast, mfcc_5, mfcc_7, and mfcc_8 had negative coefficients, suggesting an inverse relationship.

The model's explanatory power, measured by the Pseudo R^2, was 0.0229 (see Table 2). While low, this value is consistent with expectations for physiological prediction tasks using low-dimensional input features [13].

A bar plot summarizing the feature contributions is shown in Figure 3, where the direction and magnitude of each coefficient are visualized. Notably, the intercept term (cons) was excluded from the visualization to improve readability.

Table 1: The coefficients of binary logistic regression model

y	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
mfcc_1	-0.00358	0.00120	-2.98000	0.00300	-0.00594	-0.00123
mfcc_2	0.00677	0.00155	4.36000	0.00000	0.00373	0.00981
mfcc_3	0.02182	0.00154	14.14000	0.00000	0.01880	0.02485
mfcc_4	0.00545	0.00219	2.49000	0.01300	0.00115	0.00975
mfcc_5	-0.01313	0.00239	-5.50000	0.00000	-0.01781	-0.00845
mfcc_6	-0.01500	0.00285	-5.26000	0.00000	-0.02059	-0.00941
mfcc_7	-0.01573	0.00319	-4.94000	0.00000	-0.02198	-0.00949
mfcc_8	-0.01757	0.00370	-4.75000	0.00000	-0.02482	-0.01031
mfcc_9	-0.00761	0.00373	-2.04000	0.04100	-0.01491	-0.00031
mfcc_10	-0.02078	0.00414	-5.02000	0.00000	-0.02889	-0.01267
mfcc_11	-0.01935	0.00421	-4.60000	0.00000	-0.02761	-0.01110
mfcc_12	-0.02052	0.00409	-5.02000	0.00000	-0.02853	-0.01251
cons	-5.59677	0.09440	-59.29000	0.00000	-5.78180	-5.41175

Table 2: Summary Statistics of the Logistic Regression Model

Logistic regression			
	Number of obs	=	233,800
	LR chi2(12)	=	578.82
	Prob > chi2	=	0
Log likelihood = -12351.321	Pseudo R2	=	0.0229

5.2 Accuracy

The model's overall discriminative performance was evaluated using the Receiver Operating Characteristic (ROC) curve. As shown in Figure 4, the model achieved an Area Under the Curve (AUC) of 0.649, indicating moderate classification capability.

Compared to previous studies, this result is slightly better than HRV-based models, such as Fujiwara et al. [9] (estimated AUC ≈ 0.62 based on sensitivity and false positive rate) and Vicente et al. [5]. However, it remains below the performance of CNN-based facial recognition models [10,16] or EEG-based systems [2,6,19], which often report AUC values above 0.75–0.85. Nonetheless, those methods typically require intrusive or specialized sensors, whereas our method uses only passive voice input.

To supplement the ROC analysis, the confusion matrix is presented in Table 3 and visualized in Figure 5. The overall accuracy was calculated using Equation (3):

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{3}$$

Substituting the values:

$$\begin{aligned} &Accuracy \\ &= (1{,}249 + 145{,}500)/(1{,}249 + 145{,}500 + 86{,}060 + 991) \\ &= 0.621(62.1\%) \end{aligned} \tag{4}$$

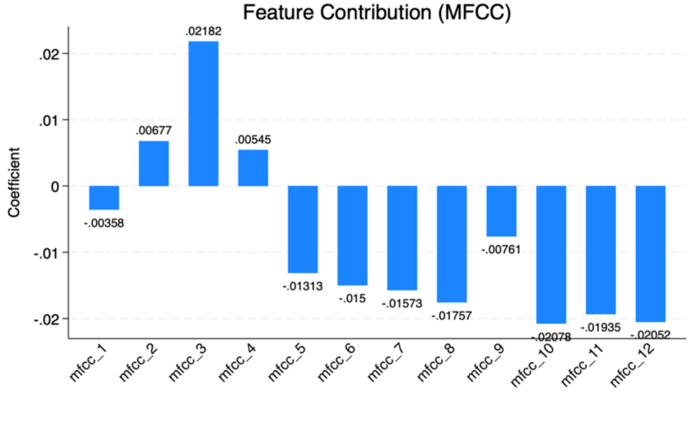

Figure 3: Feature Contribution (MFCC)

5.3 Interpretation

These results confirm the feasibility of predicting physiological states such as drowsiness from voice data. Despite the model's simplicity, it achieved moderate accuracy and AUC, using only MFCC-based acoustic features from short voice segments.

This voice-only, non-invasive approach offers a practical trade-off between accuracy and deploy ability. While the performance does not yet meet the standards required for mission-critical applications (e.g., medical diagnostics or autonomous vehicles), it is sufficient to support lightweight monitoring in work environments or as a complementary signal in multimodal systems [11,17,18].

Moreover, the results validate earlier studies suggesting a link between autonomic nervous system activity and vocal properties [3,6,10]. The successful use of voice to predict future heart rate drops—enabled by the two-hour label shifting strategy—further supports the concept of voice as a predictive bio signal.

In the next section, we outline specific directions for improving prediction accuracy, including feature engineering, deep learning integration, and real-world testing.

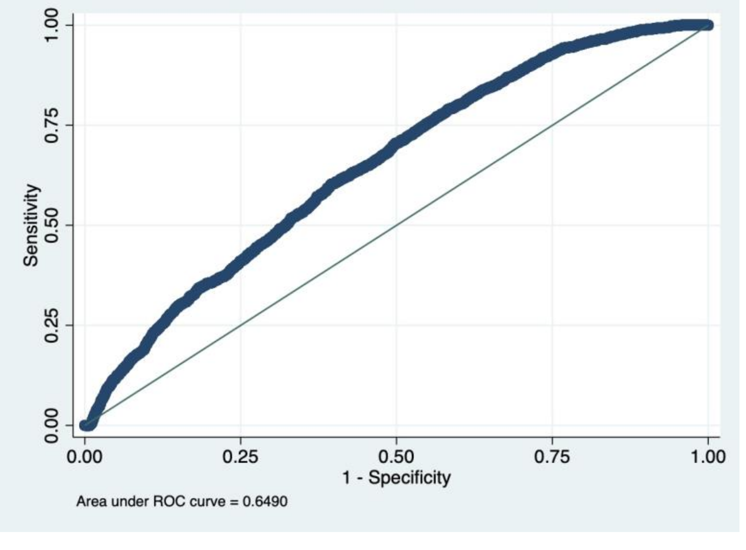

Figure 4: AUC (Area Under the Curve)

6.0 CONCLUSION

This study investigated the feasibility of predicting drowsiness using passive voice input by constructing a model that estimates the probability of future heart rate decreases—an established physiological marker of drowsiness—based on short speech recordings. Unlike traditional approaches that rely on specialized sensors or invasive measurements (e.g., EEG, HRV monitors) [6,7], the proposed method depends solely on acoustic features extracted from voice, enabling a minimally invasive and scalable solution for early drowsiness detection.

Table 3: Confusion Matrix of the Prediction Model

	Predict = 0	Predict = 1	Total
Actual = 0 (Negative)	145,500 (62.8%)	86,060 (37.2%)	231,560 (100%)
Actual = 1 (Positive)	991 (44.2%)	1,249 (55.8%)	2,240 (100%)
Total	146,491	87,309	233,800

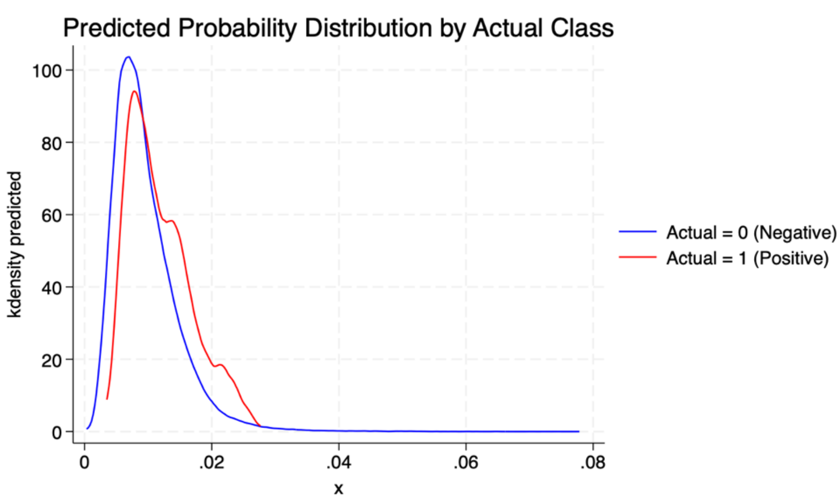

Figure 5. Confusion Matrix for Heart Rate Decrease Classification

The logistic regression model trained on MFCC features achieved an AUC of 0.649 and an accuracy of 62.1%, as demonstrated by ROC analysis (Figure 3) and confusion matrix evaluation (Table 3, Figure 4). While the predictive performance is moderate compared to advanced CNN- and EEG-based models [2,6,19], the results support the viability of using voice as a bio signal to monitor autonomic nervous system states [3,6,10].

Importantly, the study introduced several novel methodological contributions:

- Prediction of future physiological state: A two-hour forward shift was applied to heart rate labels, enabling early detection of drowsiness risk from current voice input.

- Systematic audio data augmentation: Techniques such as pitch shifting, reverberation simulation, and noise injection were employed to improve model generalization without requiring extensive datasets [2].

- Passive voice-only framework: The system requires no additional physical sensors, enhancing real-world applicability for non-intrusive deployment scenarios [11,12,17,18].

Despite these contributions, the current model's performance remains insufficient for high-stakes environments such as clinical monitoring or autonomous driving. Therefore, several future directions are proposed to enhance the system's robustness and utility:

- Advanced feature engineering: Incorporating prosodic features (e.g., intonation, rhythm, stress patterns) and spectral-temporal descriptors related to cognitive fatigue may improve prediction accuracy [6].

- Integration of deep learning architectures: End-to-end models such as CNNs or RNNs could jointly learn both feature extraction and classification, potentially surpassing manually engineered systems [2,13].

- Multimodal sensing and IoT integration: Combining voice analysis with lightweight IoT-based physiological sensors (e.g., GSR, PPG bands) may yield more accurate hybrid systems

[11,12,17,18].

- EEG-based fusion: Although more invasive, integrating EEG-derived features with voice data could substantially improve prediction reliability, especially for clinical-grade applications [19].

By addressing these areas, voice-based drowsiness detection systems may evolve into powerful, real-time safety tools for use in transportation, manufacturing, and occupational health domains.

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AUTHOR CONTRIBUTIONS

C.Y. Chong: Conceptualization, Methodology, Writing- Original Draft Preparation; N.A. Fadil: Data Analysis, Validation; F.M. Nor: Data Analysis; T.A. Abu Bakar: Result Validation, Writing-Reviewing, Editing and supervision.

CONFLICTS OF INTEREST

The manuscript has not been published elsewhere and is not under consideration by other journals. All authors have approved the review, agree with its submission and declare no conflict of interest on the manuscript.

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