It's not Just *What* You Do but also *When* You Do It: Novel Perspectives for Informing Interactive Public Speaking Training

Beatrice Biancardi[1][a], Yingjie Duan[2], Mathieu Chollet[3][b] and Chloé Clavel[2][c]

[1]*LINEACT CESI, Nanterre, France*

[2]*LTCI, Télécom Paris, IP Paris, Palaiseau, France*

[3]*School of Computing Science, University of Glasgow, Glasgow, U.K.*

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Abstract: Most of the emerging public speaking training systems, while very promising, leverage temporal-aggregate features, which do not take into account the structure of the speech. In this paper, we take a different perspective, testing whether some well-known socio-cognitive theories, like first impressions or primacy and recency effect, apply in the distinct context of public speaking perception. We investigated the impact of the temporal location of speech slices (i.e., at the beginning, middle or end) on the perception of confidence and persuasiveness of speakers giving online movie reviews (the Persuasive Opinion Multimedia dataset). Results show that, when considering multi-modality, usually the middle part of speech is the most informative. Additional findings also suggest the interest to leverage local interpretability (by computing SHAP values) to provide feedback directly, both at a specific time (what speech part?) and for a specific behaviour modality or feature (what behaviour?). This is a first step towards the design of more explainable and pedagogical interactive training systems. Such systems could be more efficient by focusing on improving the speaker's most important behaviour during the most important moments of their performance, and by situating feedback at specific places within the total speech.

1 INTRODUCTION

Soft skills have been identified as key competencies for work in the 21st century (Sharma and Sharma, 2010). Among them, public speaking constitutes a real challenge: estimates indicate that 15% to 30% of the population suffers from public speaking anxiety (Tillfors and Furmark, 2007).

The automatic evaluation of public speaking performance remains a complex task for which existing approaches still show some limitations, due to its subjectivity and the challenges posed by the multimodality of human communication. An additional problem is encountered when automatic evaluations are used to provide feedback to the user. Indeed, most of the models used to predict communicative skills, and more broadly socio-emotional behaviours, are based on "black box" models (e.g., deep neural networks), whose opacity makes them ill-suited to produce explainable feedback to users about their performance. This approach weakens the current potential of public speaking skills training applications, in particular by limiting pedagogical explanations.

In this paper, we propose a novel approach towards the aim of facilitating explainability in public speaking training systems. In particular, we are interested in whether specific moments during a speaker's speech have a different impact on the perception of their performance. If it is the case, a speaker should pay more attention at their behaviours during these specific moments. In particular, we investigate whether some well-known effects of socio-cognitive theories, such as first impressions (Ambady and Skowronski, 2008) or primacy and recency effect (Ebbinghaus, 1913), apply in the distinct context of public speaking.

We aim to answer the following research question: *"Is the impact of speakers' behaviours on the observer's perception of their performance different according to WHEN these behaviours are realised during the speech? If yes, which part of the speech is the most important?"*

[a] https://orcid.org/0000-0002-6664-6117
[b] https://orcid.org/0000-0001-9858-6844
[c] https://orcid.org/0000-0003-4850-3398

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Automatic assessment of a speaker's performance could benefit from this information by assigning different weights to different behaviours considering when they are realised during the speech. In addition, a training system could be more efficient by focusing on improving the speaker's most important behaviour during the most important moments of their performance, and by situating feedback at specific places within the total speech.

2 RELATED WORK

2.1 Public Speaking Assessment

Multi-modal modelling of public speaking in different contexts has been extensively studied. These contexts include job interviews (e.g., (Hemamou et al., 2019)), student presentations (e.g., (Nguyen et al., 2012)), academic talks (Curtis et al., 2015) or political speech (e.g., (Hirschberg and Rosenberg, 2005)). The results of these studies highlight that several behavioural descriptors can be used as cues of a good speaking performance. Among them: fundamental frequency F0, speaking rate, the use of 1st-person pronouns (Hirschberg and Rosenberg, 2005); motion energy, tense voice quality, reduced pause timings (Scherer et al., 2012); flow of speech, vocal variety, eye contact (Batrinca et al., 2013); overall speaker's movement normalised by the head movements (Curtis et al., 2015); vocal expressivity, pitch mean and the ratio of speech and pauses (Wörtwein et al., 2015). On the other hand, difluencies have been found to be negatively correlated with the speaker's performance (Strangert and Gustafson, 2008). In general, speech and lexical features perform better than visual ones, but multi-modal models achieve the best performance (Chen et al., 2015; Wörtwein et al., 2015).

The above studies analysed time-aggregated features, however a few others explored different approaches. For example, Ramanarayan et al. (Ramanarayanan et al., 2015) focused on the temporal evolution of a speaker's performance during a presentation, by including in their analyses time-series features. Haider et al. (Haider et al., 2020) proposed a novel active data representation method to automatically rate segments of full video presentations, based on unsupervised clustering. Chollet and Scherer (Chollet and Scherer, 2017) investigated the use of thin slices of behaviours (Ambady and Rosenthal, 1992) for assessing public speaking performance. Their results showed that it is possible to predict ratings of performance using audio-visual features of 10-second thin slices randomly selected from the full video. A similar effect was also found in the context of job interviews. The analyses in (Hemamou et al., 2021) on peaks of attention slices (of a duration between 0.5 and 3.3 seconds) during asynchronous job interviews showed that these slices were systematically different from random slices. They occured more often at the beginning and at the end of a response, and were better than random slices at predicting hirability.

2.2 Public Speaking Training

In addition to automatically assessing public speaking quality, several authors also focused on feedback generation to help speakers improve their performance. We can divide existing interactive systems according to the type of the temporality of the feedback provided: real-time feedback (e.g., (Damian et al., 2015; Tanveer et al., 2015; Chollet et al., 2015)) and after-speech report (e.g., (Zhao et al., 2017)). Real-time feedback can provide visual information such as graphs or icons, or can be communicated through the mean of virtual humans (as coach or virtual audience). After-speech reports usually include an interface displaying the video of the speaker's performance along with personalised feedback information.

2.3 Our Positioning

Temporal Position Matters...
We aim to investigate if the differences in the behaviours related to high and low public speaking performance are more discriminative at particular moments of the speech. Previous studies demonstrated that it is possible to predict a speaker's performance from thin slices randomly selected from a presentation (Chollet and Scherer, 2017; Nguyen and Gatica-Perez, 2015), but they did not focus on the location of these slices. Our general hypothesis is that not only what happens is important, but *when* it happens is important as well. Some previous works suggest that the moments that are most important in a speech are the beginning and the end. For example, *primacy and recency effect* (Ebbinghaus, 1913) is exploited by politicians as a persuasive strategy in their speech (e.g.,(Hongwei et al., 2020)). If the primacy and recency effect applies to our context, the discrimination between high and low performance should be related to the behaviours occurring *at the beginning and at the end* of the speech, while what happens in the middle should have less impact in the prediction of a speech quality. Differently, *first impressions* theory (Ambady and Skowronski, 2008) argues that perceivers form an impression of others at the earliest instants of an interaction (the earliest instants of the

speech in our case), and that this first impression is hard to modify subsequently. If this theory applies to our context, we should find a significant impact of the speakers' behaviour at the *beginning* of their speech, and what happens during the rest of the speech should have less impact in predicting their performance. Finally, it could be that what is important for a speaker is to maintain the listener's attention during all the speech. In this case, their behaviour at the *middle* of the speech should be more informative about their performance.

...Also when Giving Feedback

Our goal is to develop a public speaking training system, which can offer personalised after-speech reports providing localised, actionable hints on a variety of behaviours. If our hypothesis that different parts of speech vary in their importance is confirmed, then a feedback system should reflect this in the advice provided to users. Our main contribution in this paper is a step towards more explainable and pedagogical interactive systems. We propose a SHAP-based approach with the aim to provide feedback in a localised way and at the modality or feature level using a purely data-driven method.

3 METHODOLOGY

3.1 The POM Dataset

The Persuasive Opinion Multimedia (POM) dataset (Park et al., 2014) includes 1000 movie review videos obtained from a social multimedia website called ExpoTV.com. The videos are relatively short (mean duration = 93 ± 31 seconds). Each video contains a movie review given by one person talking in front of the camera. Persuasiveness and other high-level attributes and personality traits have been annotated for each speaker by three raters, on a 7-point Likert scale. The final value for each dimension is the mean of the scores given by the three raters.

3.2 Labels

In the studies presented in Section 2, most of the items used to assess a speaker's performance are explicitly related to their verbal and non-verbal behaviours. A few items are related to the raters' perception of the speakers, beyond their behaviour, and mainly concern the perceived level of *confidence* and *persuasiveness* of the speaker. We focus on these two dimensions since we are interested in how annotators' perception of the speaker is influenced by their behaviours.

As we want to discriminate between performances in terms of quality, we only consider speakers who obtained high and low scores of *persuasiveness* or *confidence*. Speakers obtaining *persuasiveness* scores higher than 5 are taken as high-persuasiveness speakers, while speakers obtaining *persuasiveness* scores lower than 3 are taken as low-persuasiveness ones. Since *confidence* ratings are a bit positively skewed, we consider scores higher than 6 to select high-confidence speakers, while speakers obtaining *confidence* scores lower than 3 are taken as low-confidence ones. The final set used in our study contains 162 high-persuasiveness, 114 low-persuasiveness, 94 high-confidence and 61 low-confidence samples.

3.3 Features

3.3.1 Audio Features

We used openSMILE (Eyben et al., 2010) to extract 88 features from the extended Geneva Minimalistic Acoustic Parameter Set (eGeMAPS) proposed by Eyben et al. (Eyben et al., 2016). This feature set includes prosodic, voice quality and some spectral features like MFCCs. The default statistical functionals (e.g., mean, standard deviation) were computed for each feature. In addition, features related to speech flow (speech and articulation rates, use of pauses) were extracted from the aligned transcripts.

3.3.2 Text Features

We counted the number of occurrences of unigrams and bigrams of the corresponding transcripts. We used lemmas of words extracted by the lemmatizer nltk (Bird et al., 2009) for unigrams and bigrams and selected unigrams and bigrams occurring more than 100 times in the corpus. We used spaCy [1] to extract POS of each word and selected unigrams, bigrams and trigrams occurring more than 20 times. We also extracted 93 features of Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al., 2015).

3.3.3 Visual Features

We used OpenFace 2.2 (Baltrusaitis et al., 2018) to extract Action Units (AU) related features of both presence and intensity (see Table 1 for more details), as well as head pose features.

3.3.4 Feature Groups

The features described above were grouped according to their modality (i.e., text, audio or visual) and also

[1] https://github.com/explosion/spaCy

Table 1: The features computed for our study, belonging to three modalities: audio, text and visual.

Audio
eGeMAPS contains 88 features: prosodic features: pitch, loudness etc. voice quality features: formant, jitter, shimmer etc. spectral features: MFCC 1-4, spectral flux etc.
Flow of Speech: speech_rate_words= $\frac{nWords+nPauses}{10}$ art_rate_words= $\frac{nWords}{10-durationPauses}$ pause_rate= $\frac{nPauses}{10}$ pause_ratio = $\frac{nPauses}{nWords}$ pause_mean_dur= $\frac{durationPauses}{nPauses}$ pause_perc= $\frac{durationPauses}{10}$

Text
LIWC contains 93 features: Syntactic related: Ppron, Verb categories etc. Lexical related: Social, Work categories etc.
Count of N-gram contains 606 features uni-grams and bi-grams of lemmas occurring >100 times
Count of POS N-gram contains 1310 features uni-grams, bi-grams and tri-grams of POS occurring >20 times

Visual

Presence of AU:
duration= $sum(AU)$
episodes= #separate episodes
average= $\frac{duration}{episodes}$

Intensity of AU: int_mean, int_sd, int_range ($\text{int}_{min} - \text{int}_{max} -$) int′_mean, int′_sd, int′_range ($\text{int}'_{min-} \text{int}'_{max}$)
Head Pose Count of Nod: number of peaks and valleys of pose_Rx Count of Shake: number of peaks and valleys of pose_Ry Count of Tilt: number of peaks and valleys of pose_Rz

Table 2: Feature Groups and Corresponding Features.

Lexical	count of n-gram and lexical related categories in LIWC
Syntactic	count of POS n-gram and syntactic related categories in LIWC
Prosody	prosodic features in enGeMAPS and features of flow of speech
Voice Quality	voice quality features in eGeMAPS
Spectral	spectral features in eGeMAPS
Facial Expression	features of presence of AU and features of intensity of AU
Head Pose	features of head pose

combined in multi-modal groups (i.e., audio+text, audio+visual, text+visual). In addition, when computing the SHAP values (see Section 4.2.2), we also categorised the features in higher-level groups. For audio features, we considered three groups: Prosody, Voice Quality and Spectral. For text features, we divided them into Lexical and Syntactic. For visual features, we categorised them into Facial Expressions and Head Poses. All the groups and corresponding features are listed in Table 2.

4 EXPERIMENTS AND RESULTS

4.1 Experimental Setting

4.1.1 Slices Datasets

To address our research question, we used thin slices to investigate the effect of different moments of the speech on the perception of the speaker. In line with previous work (e.g., (Chollet and Scherer, 2017)) we fixed the duration of the windows to 10 seconds. For each video, we extracted the following windows: *start* (the first 10s), *middle* (a 10s window randomly selected from any moment after the first 30s and before the last 30s of the video) and *end* (the last 10s). These slices were grouped in three new datasets: *start-dataset*, *middle-dataset* and *end-dataset* according to which part each slice belongs to.

4.1.2 Classification Models

The aim of this paper is not to obtain state-of-the-art performance in classification accuracy, but rather to provide insights about the importance of the various speech parts and the relative contributions of different modalities to each of these parts. Accordingly, we chose Support Vector Machine (SVM) as the baseline model to perform the following experiments. We applied feature selection methods to select the most important and relevant features, to reduce the redundant ones and improve the performance of the model. Similar to the method used in (Nojavanasghari et al., 2016), we performed a z-test between the features extracted from high and low performance instances, then select features with $p < 0.05$.

Multi-modal features were generated through early fusion.As for the hyperparameters of the model (C and γ), we selected the best combination from lists of values (the value of C varies in [1, 10, 20] and the value of γ varies in [0.001, 0.01, 0.1, 1,'auto']) using 5-fold cross validation.

For each slices dataset (i.e., *start-dataset*, *middle-dataset* and *end-dataset*) as well for the original dataset of the full videos, we took 80% as the training set and the rest as the test set. We trained models on a binary classification task (high and low *confidence* or *persuasiveness*) by using features from a single modality or combined features from different modalities, and looked at the F1-scores (because our datasets are imbalanced, see Section 3.2). Due to the relatively small size of our dataset, the F1-score varies when we use different random seeds to split the dataset. Therefore, we sampled the F1-score 300 times using different random seeds and calculated its 95% confidence interval. The results are shown in Tables 3 and 4.

4.2 Results

4.2.1 Thin Slices vs Full Video

In Tables 3 and 4, we report F1-scores on *confidence* and *persuasiveness* for different modalities and different slices of the video. In both tables, we can notice that the F1-scores vary across the different feature sets and the considered slices.

The results show that using the full video leads to a higher performance compared to the slices, in most of the cases (audio, text, audio+visual and text+visual for *confidence* ratings; audio, text, visual and audio+visual for *persuasiveness*).

What is interesting is that, for both *confidence* and *persuasiveness*, the best performance is obtained when considering the middle slice (for audio+text and all modalities and audio+text, text+visual and all modalities, respectively). In particular, the best absolute score for both *confidence* and *persuasiveness* prediction is obtained when considering audio+text features in the middle slice.

4.2.2 Temporal Location of Behaviours

With eXplainable Artificial Intelligence (XAI) developing rapidly in recent years, many excellent tools have emerged to help us interpret our models. Among them, SHAP (Shapley Additive Explanations), proposed by (Lundberg and Lee, 2017), is used to explain the output of any machine learning model, by showing how much each feature or group of features, contribute, either positively or negatively, to the target variable. The SHAP analysis on the different behavioural features can give us more details about how each behaviour is informative and *when*. In Figures 1 and 2, the mean absolute SHAP values of (a) behaviour modalities and (b) feature groups (see Table 2 for more details) are provided, relative to the models predicting *confidence* (Figure 1) or *persuasiveness* (Figure 2) quality. From these Figures, we can see that, even if in general text modality is the most informative for the models (see Figures 1a and 2a), we can notice some variations across the speech moments. For example, syntactic features are more informative to predict the speaker's *confidence* during the middle slice compared to the other moments of the speech (Figure 1b).

5 DISCUSSION

The results from Tables 3 and 4 show that in general using the entire video allows for a better performance when predicting public speaking quality, compared to specific thin slices. This is consistent with previous results in (Chollet and Scherer, 2017; Nguyen and Gatica-Perez, 2015), where it was observed that for confidence, using full video still performs better than just using thin slices.

We remind that the focus of this work is not on the use of thin slices in general but rather on the impact of the temporal position of these slices. Our aim is to analyse public speaking under the perspective of socio-cognitive theories such as primacy and recency effect or first impressions. Under this point of view, there are some results worth being discussed. In particular, the best absolute performance of the models was obtained when looking at the middle slice of the speech. This could indicate that what is important for a speaker is to maintain the audience's attention and interest also after a first impression is formed. These results are in contrast with previous findings, for example in (Hemamou et al., 2019) it was found that slices at the beginning and end of a speech performed better than random slices in predicting a speaker's hirability. The used methods and dataset are different from ours, thus more investigations are required to compare these findings.

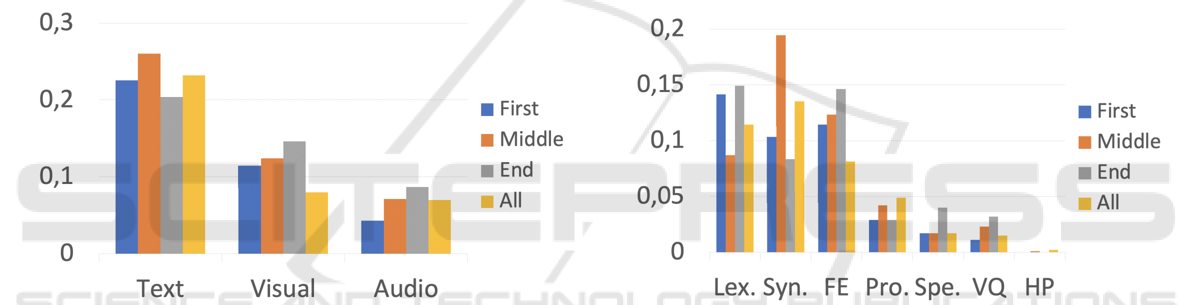
Beyond the results specific to our research question, we can notice a slightly lower performance when predicting *persuasiveness* level compared to *confidence*. This could be explained by the lower inter-raters agreement for *persuasiveness* ((Park et al., 2014)) and confirms that these dimensions, even if correlated, represent different aspects of the speaker's performance, e.g., *persuasiveness* is more related to dominance than *confidence* (Burgoon et al., 2002).

Table 3: The prediction F1-scores of confidence for different features sets of different slices.

Confidence	Start	Middle	End	Full
Audio	0.738 (0.729, 0.747)	0.761 (0.753, 0.768)	0.707 (0.699, 0.715)	**0.804** (0.797, 0.812)
Text	0.835 (0.828, 0.842)	0.882 (0.876, 0.888)	0.794 (0.786, 0.801)	**0.884** (0.878, 0.890)
Visual	**0.746** (0.739, 0.753)	0.741 (0.733, 0.748)	**0.746** (0.739, 0.753)	0.740 (0.733, 0.748)
Audio + Text	0.852 (0.845, 0.859)	**0.906** (0.901, 0.912)	0.827 (0.820, 0.834)	0.896 (0.890, 0.901)
Audio + Visual	0.782 (0.774, 0.790)	0.799 (0.792, 0.807)	0.802 (0.795, 0.810)	**0.839** (0.833, 0.846)
Text + Visual	0.865 (0.859, 0.871)	0.888 (0.882, 0.894)	0.880 (0.874, 0.886)	**0.889** (0.884, 0.895)
All	0.871 (0.865, 0.918)	**0.900** (0.895, 0.906)	0.889 (0.884, 0.895)	0.893 (0.887, 0.898)

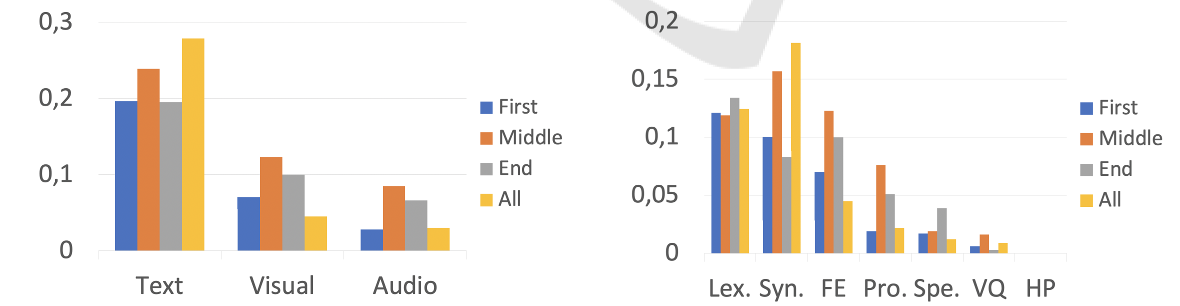
Table 4: The prediction F1-score of persuasiveness for different features sets of different slices.

Persuasiveness	Start	Middle	End	Full
Audio	0.617 (0.611, 0.623)	0.601 (0.595, 0.608)	0.624 (0.618, 0.631)	**0.702** (0.696, 0.709)
Text	0.733 (0.728, 0.739)	0.787 (0.782, 0.792)	0.727 (0.721, 0.733)	**0.800** (0.795, 0.805)
Visual	0.619 (0.613, 0.624)	0.619 (0.613, 0.624)	0.619 (0.613, 0.624)	**0.622** (0.616, 0.628)
Audio + Text	0.741 (0.736, 0.747)	**0.832** (0.827, 0.837)	0.737 (0.731, 0.742)	0.812 (0.807, 0.817)
Audio + Visual	0.641 (0.635, 0.648)	0.630 (0.623, 0.636)	0.653 (0.647, 0.659)	**0.688** (0.682, 0.694)
Text + Visual	0.763 (0.757, 0.768)	**0.831** (0.826, 0.836)	0.782 (0.776, 0.787)	0.802 (0.798, 0.807)
All	0.765 (0.760, 0.770)	**0.828** (0.823, 0.833)	0.794 (0.788, 0.780)	0.812 (0.807, 0.817)



(a) Mean absolute SHAP values of modalities. (b) Mean absolute SHAP values of feature groups.

Figure 1: Mean absolute SHAP values of (a) behaviour modalities and (b) feature groups, relative to the models prediction confidence quality using the different slices (beginning, middle or end) or the entire video (Lex.: lexical, Syn.: syntactic, FE: facial expression, Pro.: prosody, Spe.: spectral, VQ: voice quality, HP: head pose).



(a) Mean absolute SHAP values of modalities. (b) Mean absolute SHAP values of feature groups.

Figure 2: Mean absolute SHAP values of (a) behaviour modalities and (b) feature groups, relative to the models predicting persuasiveness quality using the different slices (beginning, middle or end) or the entire video (Lex.: lexical, Syn.: syntactic, FE: facial expression, Pro.: prosody, Spe.: spectral, VQ: voice quality, HP: head pose).

In addition, once again in line with results from (Park et al., 2014), and other previous works (Chen et al., 2015; Wörtwein et al., 2015) using uni-modal visual features got the lowest performance for both *confidence* (Table 3) and *persuasiveness* (Table 4) prediction. This could suggest that in public speaking assessment the non-verbal behaviours need to be contextualised according to what and how is said (i.e., in combination with text and audio modalities).

The results shown in Figures 1 and 2 also suggest the interest to leverage local interpretability of the SHAP-based approach to provide feedback directly, both at a specific time (what speech part?) and for a specific behaviour modality or feature (what behaviour?). Endowing training interactive systems with this information would allow them to provide more adapted and hopefully more useful feedback to speaker trainees. This could take the form of a report highlighting the different feature groups and associated behaviours that contributed positively and negatively to a specific assessment.

The main limitation of our study is that the results we obtained could be related to the particular characteristics of POM dataset. The duration of the videos is relatively short (93 ± 31 seconds) and the content of the speech very specific (movie reviews). In the case of longer videos, such as TED Talks [2]) for instance, other moments of the speech could be more discriminative. However, the findings of the present study still support the hypothesis that the impact of a speaker's behaviour on the perception of their performance is different according to *when* these behaviours are realised during the speech, and this should be taken into account by public speaking training systems. Further investigations could elucidate whether what happens in the middle part of the speech is still important in different contexts or whether first impressions or primacy and recency effect apply in those cases.

6 CONCLUSION

In this paper, we proposed a novel perspective to analyse public speaking performance. In order to facilitate explainability of the assessment of a speaker's performance and in turns provide more pedagogical training system, we investigated the impact of the temporal location of speech slices on the perception of confidence and persuasiveness of the speaker. We found that, when considering multi-modality, usually the middle part of speech is the most informative. In order to use model-learned knowledge to give feedback, we discussed a SHAP-based feedback approach, with the aim to provide feedback in a localised way and at the modality or feature level using a purely data-driven method.

This is a first step towards the design of more explainable and pedagogical interactive training systems. Such systems could be more efficient by focusing on improving the speaker's most important behaviour during the most important moments of their performance, and by situating feedback at specific places within the total speech. In future work, we plan to apply the same perspective by implementing more powerful models such as attention-based neural models and validate our results on larger datasets. We are also interested in whether the results also hold for longer speeches, since observer attention may vary differently.

[2]https://www.ted.com/

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