MDPE: A MULTIMODAL DECEPTION DATASET WITH PERSONALITY AND EMOTIONAL CHARACTERISTICS

Anonymous authors
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ABSTRACT

Deception detection has garnered increasing attention in recent years due to the significant growth of digital media and heightened ethical and security concerns. It has been extensively studied using multimodal methods, including video, audio, and text. In addition, individual differences in deception production and detection are believed to play a crucial role.Although some studies have utilized individual information such as personality traits to enhance the performance of deception detection, current systems remain limited, partly due to a lack of sufficient datasets for evaluating performance. To address this issue, we introduce a multimodal deception dataset MDPE. Besides deception features, this dataset also includes individual differences information in personality and emotional expression characteristics. It can explore the impact of individual differences on deception behavior. It comprises over 104 hours of deception and emotional videos from 193 subjects. Furthermore, we conducted numerous experiments to provide valuable insights for future deception detection research. MDPE not only supports deception detection, but also provides conditions for tasks such as personality recognition and emotion recognition, and can even study the relationships between them. We believe that MDPE will become a valuable resource for promoting research in the field of affective computing.

1 INTRODUCTION

Generally, deception refers to the act of misleading, tricking, or deceiving others DePaulo et al. (2003). It involves hiding the truth or presenting false information to create an impression that is not accurate. Deception can take many forms, including both verbal and nonverbal information Burgoon et al. (2021). And it also occurs in various contexts, such as interpersonal relationships, business, politics, and entertainment. Deception is often considered unethical and can have serious consequences for trust and relationships.

As deception has expanded to other fields such as social media, interviews, online transactions, and deception in daily life,the need arises for a reliable and efficient system to aid the task of detecting deceptive behavior. Many machine learning approaches have been proposed in order to improve the reliability of deception detection systems Granhag & Hartwig (2008). In particular, physiological, psychological, visual, linguistic, acoustic, and thermal modalities have been analyzed in order to detect discriminative features and clues to identify deceptive behavior Feng et al. (2012); Hirschberg et al. (2005); Newman et al. (2003); Rajoub & Zwiggelaar (2014). Video-based deception detection is a current priority in deception research, because behavioral cues can be extracted from videos in a cheaper, faster, and non-invasive manner Burzo et al. (2018), which is preferable to invasive approaches that extract clues through devices attached to human bodies (e.g., polygraphs). Visual clues of deception include facial emotions, expression intensity, hands and body movements, and microexpressions. These features were shown to be capable of discriminating between deceptive and truthful behavior Ekman (2009); Owayjan et al. (2012). Acoustic features took into account the pitch and speaking rate among other measurements to specify whether certain features are associated with an act of deceit Hirschberg et al. (2005). Linguistic features were usually extracted from the language, words usage, and consistency of the statements made by a person Howard & Kirchhübel (2011). Recently, multimodal analysis has gained a lot of attention due to their superior performance compared to the use of unimodal modalities. In the deception detection field, several multimodal approaches Pérez-Rosas et al. (2015); Krishnamurthy et al. (2018); Şen et al. (2020); Mathur &

Matarić (2020) have been suggested to improve deception detection by integrating features from different modalities. This integration created a more reliable system that is not susceptible to factors affecting sole modalities and polygraph tests.

In addition, it is firmly believed that there are individual differences in deception production and detection Levitan et al. (2015); Majumder et al. (2017); Ren et al. (2021). Specifically, it includes cognitive level, personality traits, psychological characteristics, and emotional expression. Everyone has different personalities and psychological characteristics, and the expression of emotions is also various. It has been demonstrated through several studies that personality factors and emotional cues play a significant role in subjects' ability to deceive and detect deception Levitan et al. (2015); Gaspar & Schweitzer (2013). Emotion is a fundamental aspect of human communication that interacts with cognition, guiding social behavior in both human-to-human interactions and human-computer interactions Gordon et al. (2016); Marchi et al. (2015). Emotional characteristics are important, because deceptive behavior can trigger emotional states, leading to behavioral changes that serve as deceptive clues Ekman (2009); Vrij (2008). However, it is difficult to directly improve the accuracy of deception detection using emotional features Hartwig & Bond Jr (2014). One of the reasons is that emotional expression is also a part of deception. It is usually difficult to detect whether a deceiver's emotional expression is genuine or disguised.

To address this issue, we propose a multimodal deception dataset MDPE. It not only collects subjects' deception information, but also personality information and emotional expression information. Each subject was required to conduct another emotional experiment in addition to engaging in deception, in order to obtain their true emotional expression. Although our research was conducted in the laboratory to provide clear and comparable conversations, we provided subjects with effective monetary incentives to detect and generate effective deceptive behavior Levitan et al. (2015). To our knowledge, this is the largest multimodal deception dataset in the released dataset and the only deception detection dataset with personality and emotional characteristics.

To sum up, our contributions are threefold:

- We propose a novel multimodal deception dataset MDPE with personality and emotional characteristics, composed of facial video, and audio recordings and transcript. And an easily replicable experimental protocol has also been provided to researchers.
- We provide a benchmark for deception detection from multimodal signals, and discussed the impact of personality traits and emotional cues on deception detection.
- We offer new possibilities to facilitate further affective computing research, encourage the development of new methods that utilize individual differences for deception detection, as well as for tasks such as personality recognition and emotion recognition.

2 Related Work

Deception Dataset Pérez-Rosas et al. Pérez-Rosas et al. (2015) introduced a new multi-modal deception dataset Real-life Trial having real-life videos of courtroom trials. They demonstrated the use of features from different modalities and the importance of each modality in detecting deception. They also evaluated the performance of humans in deception detection and compared it with their machine learning models. The Box-of-Lies dataset Soldner et al. (2019) was released with video and audio from a game show, and presents preliminary findings using linguistic, dialog, and visual features. Multiple modalities have been introduced in the hope of enabling more robust detection. Pérez-Rosas et al. Pérez-Rosas et al. (2014) introduced a dataset for deception including video and thermal imaging, as well as physiological and audio recordings. Gupta et al. Gupta et al. (2019) proposed Bag-of-Lies, a multimodal dataset with gaze data for detecting deception in casual settings. Speth Jeremy et al.Speth et al. (2021) proposed a multimodal deception database DDPM contains almost 13 hours of recordings of 70 subjects, as well as physiological signals such as thermal video frames and pulse oximeter data. Most studies on deception detection are designed and evaluated on private datasets, typically with relatively small sample sizes, and MDPE dataset addresses these drawbacks. Table 1 compares the sample size and length for existing datasets and MDPE.

Multimodal Deception Detection Decades of research in psychology, and deception detection have documented verbal and nonverbal behavioral cues indicative of deceptive communication. Visual cues

Table 1: Comparison of the subject count and length for several databases for deception detection

dataset	Subjeet Count	Length(Minutes)
Multimodal	30	-
Real Trials	56	56
Box-of-Lics	26	144
Bag-of-Lies	35	<241
DDPM	70	776
MDPE	193	6209

such as the frequency and duration of eye blinks Bhaskaran et al. (2011); Fukuda (2001); Minkov et al. (2012), dilation of pupils Dionisio et al. (2001); Lubow & Fein (1996), and facial muscle movements Hurley & Frank (2011); Porter et al. (2011) have been found to distinguish between deceptive and truthful behavior. Vocal cues can be indicative of deception, with deceptive speakers tending to speak with higher and more varied pitch DePaulo et al. (2003); Zuckerman et al. (1981), shorter utterances, and less fluency Rockwell et al. (1997); Sporer & Schwandt (2006) than truthful speakers. Deception also correlates with verbal attributes of speech, with deceivers tending to communicate with less cognitive complexity, fewer self-references, and more words indicative of negative emotions Zhou et al. (2004); Newman et al. (2003). Mohamed Abouelenien et al. Abouelenien et al. (2016) explored a multimodal deception detection approach and integrates multiple physiological, linguistic, and thermal features. They used a decision tree model, to gain insights into the features that are most effective in detecting deceit. Leena Mathur et al. Mathur & Matarić (2020) analyzed the discriminative power of features from visual, vocal, and verbal modalities affect for deception detection. They experimented with unimodal Support Vector Machines (SVM) and SVM-based multimodal fusion methods to identify effective features for detecting deception.

Individual Difference Deception Some studies confirm that some of the five NEO-FFI (Neuroticism-Extraversion-Openness Five-Factor Inventory) dimensions are related to deception Ramanaiah et al. (1994); Jakobwitz & Egan (2006). Sarah Ita Levitan et al. Levitan et al. (2015) reported the role of personality factors derived from the NEO-FFI and of gender, ethnicity and confidence ratings on subjects' ability to deceive and to detect deception. Justyna Sarzyńska et al. Sarzyńska et al. (2017) reports correlations between the ability to lie and extraversion, as well as conscientiousness. Personality characteristics are a promising set of information for deception detection, and similarly, emotional characteristics are also important. Joseph P. Gaspar et al. Gaspar et al. (2022) integrate prior theory and research on emotions, emotional intelligence, and deception and introduce a theoretical model. This model explores the interplay between emotional intelligence (the ability to perceive emotions, use emotions, understand emotions, and regulate emotions; and deception. Mircea Zloteanu et al hold strong beliefs about the role of emotional cues in detecting deception, and explored how decoders' emotion recognition ability and senders' emotions influence veracity judgements Zloteanu et al. (2021). Joseph P. Gaspar et al. Gaspar & Schweitzer (2013) believe that emotions are both an antecedent and a consequence of deception, and they introduce the emotion deception model to represent these relationships. This model broadens their understanding of deception in negotiations and accounts for the important role of emotions in the deception decision process. To our knowledge, MDPE is the only deception detection dataset with personality and emotional characteristics.

3 Dataset

3.1 Materials

We collect our deception dataset using: a sports camera Gopro Hero9 with a resolution of 1920x1080 and a frame rate of 60 fps. The voices of the subjects are also recorded by the built-in microphone of the camera. A Thinkpad laptop was provided to subjects for watching emotion induction videos during the emotion experiment. The experimental place is in a professional recording stdio, and during the data collection process, only the subject and interviewer stay in the room. Some materials were prepared by the Data Collection Coordinator (DCC). The experimental setup is shown in Figure 1.

(a) Deception Experiment (b) Emotional Experiment

Figure 1: The example of the place setup for data acquisition.

3.2 Participants

There were 193 subjects in this study, of which 130 were female and 63 were male. They are all native Chinese speakers from different backgrounds. Their age ranged from 18 to 69 years old, and they had various professions including students, workers, teachers, retirees, etc.

Firstly, we segmented the raw video, resulting in 1808 minutes of deceptive video and 4401 minutes of emotional video, totaling 6209 minutes. Each of the 193 subjects provided 24 responses, 9 of which were deceptive. The length of deception videos ranged from 4 minutes to 27 minutes. Each subject had 16 emotional videos, with lengths ranging from 19 minutes to 38 minutes (including the time spent watching emotional induction videos).

Before the experiment began, the subjects were informed of all experimental procedures. The subjects explicitly consented to record their conversation and publish the video data in a scientific conference or journal. And we do not publish any privacy sensitive data, and the anonymity of participants will be guaranteed. All data were collected under a protocol approved by the authors'institution's Human Subjects Institutional Review Board.

3.3 Procedure

Personality Characteristics Collection: Subjects were required to fill out a Big Five personality questionnaire Zhang et al. (2022), which consists of 60 questions. Each question was marked with a score indicating whether the descriptions match their own, with 1 indicating strong disagreement and 5 indicating strong agreement. Details can be found in the appendix A.

Emotional Experiment: Subjects were asked to watch 16 emotional induction videos, including two induction videos for each emotion of sadness, happiness, relaxation, surprise, fear, disgust, anger, and neutral. There are a total of 39 induction videos, of which 17 are from the Chinese Emotional Video System (CEVS) et al. (2010). Each video segment has been labeled and evaluated to ensure that it can induce corresponding emotions. Another 22 are from our online collection. Because the CEVS only include six emotions: sadness, happiness, fear, disgust, anger, and neutral, and some videos of the CEVS are outdated and cannot successfully induce corresponding emotions in our pre-experiments. Each video we collected online was annotated by 12 data annotators based on CEVS selection criteria and evaluation methods, and the results showed that each video triggered strong emotions.

Before the emotional experiment began, the DCC randomly selected 16 induction videos (ensure two videos for each emotion) for the subjects to watch. After watching each video, subjects were required to describe their feelings and then fill out an "Emotional Scale", which quantified 8 emotions. Subjects rated their 8 emotions, ranging from 1 to 5, with 1 indicating no such emotion and 5 indicating the strongest emotion. Details of the emotion scale can be found in the appendix B.

Deception Experiment: The deception data collection process follows DDPM Speth et al. (2021). The interviewer conducted an interview with the subject, asking a total of 24 questions. These 24 questions were jointly formulated by 5 psychology researchers with over 5 years of experience. Before the interview, details of the emotion scale can be found in the appendix C. The DDC randomly selected 9 questions that must lie and hand them over to the subject (the interviewer does not know which 9 questions). The first 3 questions will not be selected, which means that the first three “warm up” questions were always to be answered honestly. They allowed the subject to get settled, and gave the interviewer an idea of the subject’s demeanor when answering a question honestly.

The subject have a maximum of 15 minutes to prepare, and during the preparation process, they must remember these 9 questions and think about how to deceive in the upcoming interview process. During the interview process, when asked these 9 questions, the subject must lie, and when asked the remaining 15 questions, they must tell the truth. Subjects were motivated to deceive successfully through two levels of bonus compensation: if they were able to deceive the interviewer in five or six of the nine deceptive responses, they were given a 150 percent of a base incentive payment; the base payment was doubled if they were successfully deceptive in seven or more questions. In order to collect more indistinguishable deception answers, we encourage subjects to incorporate some truth into lies when answering these deceptive questions.

During the interview process, the interviewer asked 24 questions in random order, and provide their judgment of truthful or deceptive answers to each question. And the interviewer filled out the "Interviewer Judgment Scale", which record the trust level the interviewer thinks of each answer. The trust level was divided into 1-5 points, where 1 represents definitely true and 5 represents definitely false. After the interview, the subject also filled out the "Subject Lie Confidence Scale" and be asked to rate the answer they just lied to. The same score is 1-5, where 1 represents that I have definitely deceived successfully and 5 represents that I have definitely not deceived successfully.

Each subject was required to complete the above three experiments, so that we can obtain their personality , emotional and deceptive characteristics.

4 BENCHMARK

4.1 DATA PREPROCESSING

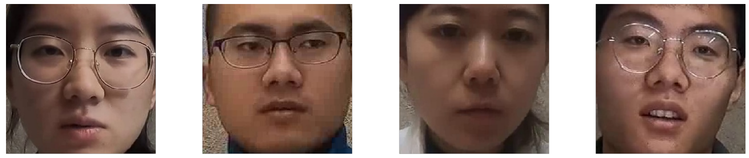
For the visual modality, we first unify the raw video to 30 fps of the frame rate, and crop and align faces via DLib Toolkit King (2009). Figure 2 shows some examples of real and deceptive faces. Then, we use visual encoders to extract frame-level , followed by average pooling to compress them to the video level. For the audio modality, we use FFmpeg to separate the audio from the video and unify the audio format to 16kHz and mono. For the textual modality, we first extract transcript using Paraformer Gao et al. (2022), an open-source ASR toolkit. After data preprocessing, for each sample x_i, we extract acoustic features $f_i^a \in \mathbb{R}^{d_a}$, textual features $f_i^l \in \mathbb{R}^{d_l}$, and visual features $f_i^v \in \mathbb{R}^{d_v}$, where $\{d_m\}_{m\in\{a,l,v\}}$ is the feature dimension for each modality.

4.2 FEATURE EXTRACTION

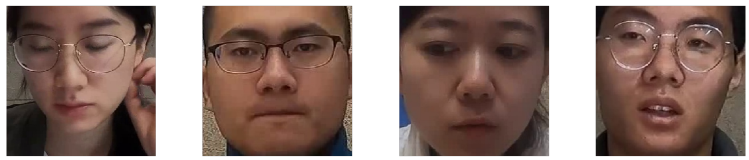
Different features lead to distinct results. To guide feature selection, we evaluate the performance of different features under the same experimental setup.

Visual Modality: Compared with handcrafted features, deep features extracted from supervised models are useful for facial expression recognition Li & Deng (2020). CLIP Radford et al. (2021) is a multimodal model based on contrastive learning, where training utilizes text and images to construct positive and negative sample pairs. Pre-training is conducted on a dataset comprising 400 million pairs, resulting in strong generalization capabilities. And Vision Transformer (ViT) Dosovitskiy et al. (2020) is a transformer encoder model , pre-trained in a supervised manner on a large dataset of images. Images are presented to the model in the form of sequences of fixed-size patches (resolution of 16x16) and undergo linear embedding.

Acoustic Modality: We extracted the handcrafted feature extended Geneva Minimalistic Acoustic Parameter Set (eGeMAPS) Eyben et al. (2015), which contains 88 acoustic parameters designed specially for speech emotional recognition tasks, covering spectral, cepstral, and prosodic features . And Wav2vec Baevski et al. (2020) demonstrates the power of learning robust representations solely from speech audio, fine-tuning on transcribed speech, surpassing the best semi-supervised methods. It masks speech inputs in the latent space and addresses a contrastive task defined on quantized latent representations. It has been widely applied to downstream speech tasks. HUBERT Hsu et al.



(a) Truth



(b) deception

Figure 2: Some examples of truth and deception faces.

(2021) utilizes offline clustering steps to provide aligned target labels for prediction losses. A key component of this approach is applying prediction losses only in masked regions, forcing the model to learn representations that combine acoustic and language models on contiguous inputs. To better distinguish between speakers, a sentence mixture training strategy WavLM Chen et al. (2022) is proposed, allowing for the unsupervised creation and merging of additional overlapping sentences during the training process.

Text Modality: Among all language models, BERT Devlin et al. (2018) and its variants are widely utilized, and it uses the masked language model and next sentence prediction objectives to learn word embeddings. Here, we extract the sbert-chinese-general-v2 features, which is based on the bert-base-chinese version of the BERT model and is trained on the million-level semantic similarity data set SimCLUE. ChatGLM Du et al. (2021) is an open-source conversational language model supporting bilingual question answering in both Chinese and English, based on the General Language Model (GLM) architecture. It demonstrats exceptional contextual understanding and more efficient inference capabilities. Baichuan Yang et al. (2023) is an open-source large-scale model with 13 billion parameters. It features a larger size, more extensive training data, and more efficient inference capabilities.

4.3 Model Structure

For unimodal features, we utilize the fully-connected layers to extract hidden representations and predict deception:

$$h_i^m = \text{ReLU}\left(f_i^m W_m^h + b_m^h\right), m \in \{a, l, v\} \tag{1}$$

$$\hat{y}_i = \text{softmax}\left(h_i^m W_m^d + b_m^d\right), m \in \{a, l, v\} \tag{2}$$

where $h_i^m \in \mathbb{R}^h$ is the hidden feature for each modality, $d_i \in \mathbb{R}^2$ is the estimated deception probabilities. For multimodal features, different modalities contribute differently to deception detection. Therefore, we compute importance scores $\alpha_i \in \mathbb{R}^{3\times 1}$ for each modality and exploit weighted fusion to obtain multimodal features:

$$h_i = \text{Concat}\left(h_i^a, h_i^l, h_i^v\right) \tag{3}$$

$$\alpha_i = \text{softmax}\left(h_i^T W_\alpha + b_\alpha\right) \tag{4}$$

Table 2: Unimodal results on MDPE. "P" denotes the addition of personality features,"E" denotes the addition of emotional features

Feature	Accuracy	AUC	with P		with E		with P and E	
			Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
VIT	60.30%	0.577	61.27%	0.582	61.43%	0.615	61.55%	0.620
CLIP-base	58.54%	0.602	59.17%	0.611	58.32%	0.606	59.11%	0.605
CLIP-large	57.30%	0.574	58.34%	0.582	56.97%	0.555	57.67%	0.579
eGeMAPS	55.86%	0.563	57.22%	0.588	56.22%	0.577	56.89%	0.585
HUBERT-base	58.13%	0.615	62.38%	0.651	59.35%	0.617	62.12%	0.641
HUBERT-large	60.80%	0.636	62.07%	0.646	60.34%	0.621	61.87%	0.644
Wav2vec2-base	58.75%	0.581	59.74%	0.603	59.99%	0.594	59.84%	0.599
Wav2vec2-large	60.10%	0.582	61.88%	0.617	59.32%	0.592	62.10%	0.634
WavLM-base	61.66%	0.609	60.82%	0.606	60.16%	0.595	60.92%	0.593
WavLM-large	57.82%	0.599	60.31%	0.583	58.02%	0.607	60.52%	0.611
Sentence-BERT	61.76%	0.639	62.34%	0.651	63.21%	0.641	63.34%	0.657
ChatGLM2-6B	60.73%	0.648	61.45%	0.659	61.45%	0.667	61.56%	0.676
Baichuan-13B	**61.87%**	**0.649**	**62.90%**	**0.667**	**63.32%**	**0.675**	**63.74%**	**0.683**

4.4 Features Fusion

For personality and emotional expression features, we use concatenation for feature fusion. To represent personality traits, we utilize the scores derived from established personality scales, which provide a quantitative measure of individual characteristics. These scores serve as our primary personality features, capturing a broad spectrum of traits such as openness, conscientiousness, extraversion, agreeableness, and neuroticism.

For the emotional expression features, our process begins with training a dedicated emotion recognition model. This model is designed to analyze and interpret various emotional cues present in the input samples. We feed a comprehensive set of emotional expression features into this model, allowing it to learn and adapt to the nuances of emotional communication. Once the model has been trained, we extract features from the last fully connected layer, which encapsulates the learned representations of emotional expressions. To refine these features further, we apply average pooling, which helps in summarizing the information across different samples, yielding a robust representation of emotional expression. The resulting concatenated feature set, combining both personality and emotional expression elements, offers a rich and multidimensional view of individual behavior and emotional states.

4.5 Implementation Details

We select the dimension of latent representations from $\{64, 128, 256\}$. During training, we use the Adam Kingma & Ba (2014) optimizer and choose the learning rate from $\left\{10^{-3}, 10^{-4}\right\}$. We set the maximum number of epochs to 300 and the weight decay to 10^{-5}. Dropout Srivastava et al. (2014) is also employed, and we select the rate from $\{0.2, 0.3, 0.4, 0.5\}$ to alleviate the over-fitting problem. We randomly select 5 answers (3 truths and 2 deceptions) from 24 answers in all samples as the validation set, and the remaining 19 answers as the training set. To mitigate randomness, we run each experiment five times and report the average result. And we choose the cross-entropy as loss function and the accuracy and AUC as the evaluation metric.

4.6 Experiment Results

Unimodal Results In this section, we establish the unimodal benchmark for MDPE and report results in Table 2. We hope this benchmark can provide guidance for feature selection and point the way to developing powerful feature extractors. For the visual modalities, VIT achieves better results than CLIP, possibly because VIT is trained on supervised datasets and can reveal more deceptive clues than CLIP features that use text as a supervisory signal. For the acoustic modality, the deep features outperform handcrafted features. This may be because egemas are features related to emotions, using a emotion-related handcrafted acoustic feature may limit performance. In contrast, deep features can capture more universal acoustic representations for deception detection. For the textual modality,

Table 3: Multimodal results on MDPE. We select several well-performing unimodal features and report their fusion results. Here, “V”, “A” and “T” represent the visual, acoustic and textual modalities, respectively.

V	A	T	Accuracy	AUC	with P		with E		with P And E	
					Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
VIT	HBB	-	61.76%	0.628	61.53%	0.617	61.14%	0.616	62.68%	0.628
VIT	WMB	-	60.88%	0.611	60.22%	0.599	60.02%	0.599	60.72%	0.587
CLB	HBB	-	61.02%	0.618	60.14%	0.606	60.53%	0.614	61.45%	0.625
VIT	-	Bai	63.31%	0.664	63.47%	0.678	63.31%	0.676	63.48%	0.672
CLB	-	Bai	63.31%	0.666	63.52%	0.677	63.38%	0.667	63.10%	0.664
CLL	-	Bai	64.15%	0.665	63.94%	0.679	63.98%	0.672	64.04%	0.678
-	HBL	Bai	62.69%	0.658	63.42%	0.665	63.00%	0.665	63.42%	0.663
-	W2B	Bai	63.83%	0.663	63.48%	0.663	63.57%	0.668	63.79%	0.664
-	WMB	Bai	64.25%	0.661	64.15%	0.679	63.90%	0.677	64.07%	0.679
VIT	HBB	Bai	**64.45%**	**0.675**	64.33%	0.679	63.93%	0.674	64.00%	0.675
VIT	WMB	Bai	63.42%	0.666	**64.87%**	**0.681**	63.62%	0.664	63.59%	0.672
CLB	HBB	Bai	62.94%	0.657	63.93%	0.678	**63.97%**	**0.678**	**64.66%**	**0.687**

we focus on textual encoders that support Chinese (large language models are generally trained on multilingual corpora containing Chinese). And the textual modality can achieve best performance than the visual and acoustic modalities, which indicates that our dataset textual reveals more deceptive clues than other modalities.

Of course, we have also incorporated personality and emotional features into deception detection. Models trained with personality features almost often exhibit superior performance. These findings demonstrate the importance of personality in deception detection tasks. And the addition of emotional features has also improved the performance of deception detection models, but the improvement is not comparable to personality features, even some results have decreased. This may be because personality traits are directly usable features, and emotional features are extracted by emotion recognition models. The quality of features is also influenced by the emotion recognition models. In the future, better methods for using emotional expression features can be explored. By incorporating both personality and emotional features, the deception detection model achieved the highest performance in unimodal results, These results show that personality and emotional expression characteristics are indeed important for deception detection tasks, and using them can truly achieve deception detection modeling based on individual differences. It is worth mentioning that among all the unimodal results, Baichuan always achieved the best results. It is the model with the largest number of parameters among the features we used, and it further demonstrates the potential of large language models in deception detection.

Multimodal Results In Table 3, we select several well-performing unimodal features and report their fusion results. Experimental results demonstrate that multimodal fusion consistently improves performance. The reason lies in the fact that deception cues can be conveyed through multiple modalities. The integration of multimodal information allows the model to better comprehend the video content and accurately detection deception. Firstly, almost all features have achieved performance improvements in multimodal feature fusion, but the fusion of visual and acoustic modalities has hardly improved or even declined. It indicates that the addition of text features make the performance of the model tend to stabilize. This is consistent with human judgment. When people judge whether others are lying, they tend to express the truth or falsehood of the content, because it difficult to judge from visual or acoustic features. In the future, further exploration and research should be conducted on deceptive clues in visual and acoustic features.

Similar to unimodal results, models trained with personality features typically exhibit excellent performance. The addition of emotional features makes the performance of the model unstable. Some features have been improved, while others have decreased. Finally, the best result always comes from the three modalities fusion, and the three modalities fusion with personality and emotional characteristics has achieved the best performance.

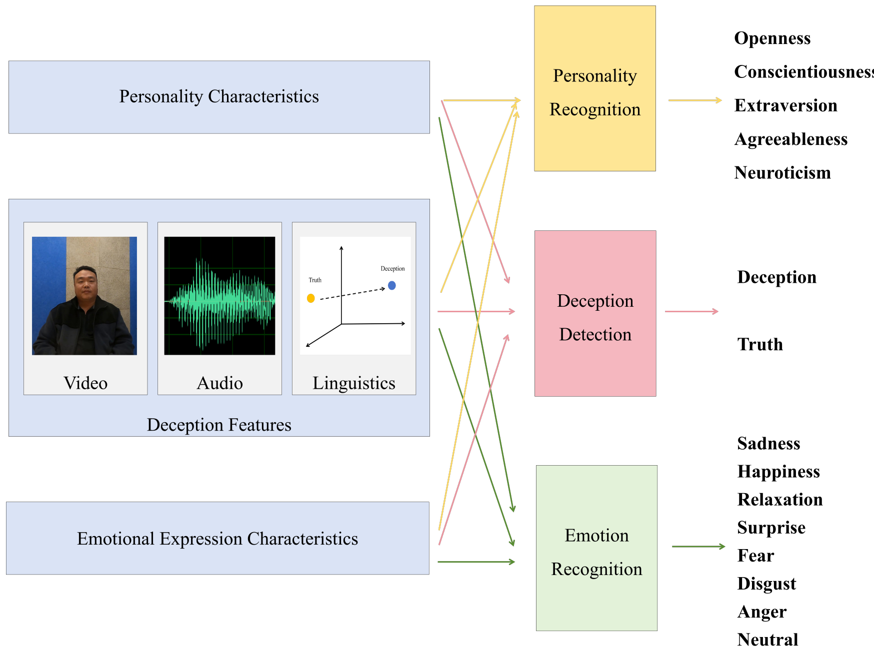


Figure 3: Possible future work on the MDPE

5 Discussion

5.1 Future work

Firstly, dimensional emotions are also important. In fact, we are labeling MDPE with dimensional emotions (including deception and emotion), which can not only study the impact of dimensional emotional features on lie detection at the individual level, but also explore more emotional clues in the deception process. Secondly, we extracts deep features from some pre-trained models and uses simple models for deception detection. In the future,larger models should be designed to be used for deception detection tasks. Thirdly, this article simply concatenates personality and emotional expression features to assist in deception detection tasks. In the future, more complex feature fusion or model fusion algorithms can be used for deception detection. Finally, in this paper, we only focuses on deception detection tasks, but MDPE includes individual personality, deception, and emotional expression information, which can not only support deception detection tasks, but also tasks such as personality recognition and emotion recognition. Even these individual level information can be used to assist other tasks, as shown in Figure 3. In fact, there have been many studies on the relationship between personality and emotion Hughes et al. (2020); Li et al. (2022); Zhang et al. (2019), but the lack of relevant datasets has led to slow research progress in this field, and we believe that MDPE can provide valuable resources for these research directions.

5.2 Limitations

Firstly, although the subjects were required that they must lie about the deception questions, and verified the deceptive questions and content with the Interviewer after the deception experiment, we do not know whether the subjects have actually deceived on the deception questions. Secondly, although our induction videos have been annotated by professionals to demonstrate their reliability and validity, there are still some subject whose feelings are inconsistent with the emotions we expected to induce. This is because different people have different understandings of the video content, triggering different emotions. Thirdly, relying on self-assessment scales for data annotation is a subjective process for subjects, which may lead to bias in subsequent analysis. Different subjects may have significant differences in their perception of emotions. In addition, MDPE only collects native Chinese speakers, there may be cultural differences in deception detection. Finally, gender imbalance among subjects in MPDE is a common issue in human data collection D'Mello et al. (2022); Pinho-Gomes et al. (2022).

6 Conclusion

We present MDPE, a dataset for deception detection featuring three categories of data modalities, as well as personality and emotional characteristics. Firstly, diverse modalities carry complementary information that can be jointly exploited. By providing access to multiple synchronized modalities, MDPE enables cross-modal analyses that have the potential to improve the understanding of the relationships between video, audio, and text. Secondly, it can help improve the understanding of deceive behavior, aiming to develop reliable deception detection algorithms and enhance the security issues related to deception in our society. Thirdly, MDPE provides the personality traits and emotional expression characteristics of each subject, which can help analyze the impact of personality and emotional expression on deceive behavior. In addition, MDPE not only supports deception detection models, but also provides conditions for personality recognition and emotion recognition tasks, and can even study the relationship between deception, personality, and emotion, such as using personality features to improve the performance of emotion recognition tasks. Finally, to promote reproducibility, MDPE also provided a set of benchmark experiments. Although the proposed model focuses on deception detection, the use of personality and emotional features also demonstrates the predictive potential of our dataset. They represent a good starting point for future work that researchers and developers can use as a benchmark. By openly sharing MDPE, we hope to ignite new advances in this critical area of affective computing.

References

Mohamed Abouelenien, Verónica Pérez-Rosas, Rada Mihalcea, and Mihai Burzo. Detecting deceptive behavior via integration of discriminative features from multiple modalities. *IEEE Transactions on Information Forensics and Security*, 12(5):1042–1055, 2016.

Alexei Baevski, Yuhao Zhou, Abdelrahman Mohamed, and Michael Auli. wav2vec 2.0: A framework for self-supervised learning of speech representations. *Advances in neural information processing systems*, 33:12449–12460, 2020.

Nisha Bhaskaran, Ifeoma Nwogu, Mark G Frank, and Venu Govindaraju. Lie to me: Deceit detection via online behavioral learning. In *2011 IEEE International Conference on Automatic Face & Gesture Recognition (FG)*, pp. 24–29. IEEE, 2011.

Judee K Burgoon, Valerie Manusov, and Laura K Guerrero. *Nonverbal communication*. Routledge, 2021.

Mihai Burzo, Mohamed Abouelenien, Veronica Perez-Rosas, and Rada Mihalcea. Multimodal deception detection. In *The Handbook of Multimodal-Multisensor Interfaces: Signal Processing, Architectures, and Detection of Emotion and Cognition-Volume 2*, pp. 419–453. 2018.

Sanyuan Chen, Chengyi Wang, Zhengyang Chen, Yu Wu, Shujie Liu, Zhuo Chen, Jinyu Li, Naoyuki Kanda, Takuya Yoshioka, Xiong Xiao, et al. Wavlm: Large-scale self-supervised pre-training for full stack speech processing. *IEEE Journal of Selected Topics in Signal Processing*, 16(6): 1505–1518, 2022.

Bella M DePaulo, James J Lindsay, Brian E Malone, Laura Muhlenbruck, Kelly Charlton, and Harris Cooper. Cues to deception. *Psychological bulletin*, 129(1):74, 2003.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.

Daphne P Dionisio, Eric Granholm, William A Hillix, and William F Perrine. Differentiation of deception using pupillary responses as an index of cognitive processing. *Psychophysiology*, 38(2): 205–211, 2001.

Anila M D'Mello, Isabelle R Frosch, Cindy E Li, Annie L Cardinaux, and John DE Gabrieli. Exclusion of females in autism research: Empirical evidence for a "leaky" recruitment-to-research pipeline. *Autism Research*, 15(10):1929–1940, 2022.

Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*, 2020.

Zhengxiao Du, Yujie Qian, Xiao Liu, Ming Ding, Jiezhong Qiu, Zhilin Yang, and Jie Tang. Glm: General language model pretraining with autoregressive blank infilling. *arXiv preprint arXiv:2103.10360*, 2021.

Paul Ekman. *Telling lies: Clues to deceit in the marketplace, politics, and marriage (revised edition)*. WW Norton & Company, 2009.

Florian Eyben, Klaus R Scherer, Björn W Schuller, Johan Sundberg, Elisabeth André, Carlos Busso, Laurence Y Devillers, Julien Epps, Petri Laukka, Shrikanth S Narayanan, et al. The geneva minimalistic acoustic parameter set (gemaps) for voice research and affective computing. *IEEE transactions on affective computing*, 7(2):190–202, 2015.

Song Feng, Ritwik Banerjee, and Yejin Choi. Syntactic stylometry for deception detection. In *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pp. 171–175, 2012.

Kyosuke Fukuda. Eye blinks: new indices for the detection of deception. *International Journal of Psychophysiology*, 40(3):239–245, 2001.

Zhifu Gao, Shiliang Zhang, Ian McLoughlin, and Zhijie Yan. Paraformer: Fast and accurate parallel transformer for non-autoregressive end-to-end speech recognition. *arXiv preprint arXiv:2206.08317*, 2022.

Joseph P Gaspar and Maurice E Schweitzer. The emotion deception model: A review of deception in negotiation and the role of emotion in deception. *Negotiation and Conflict Management Research*, 6(3):160–179, 2013.

Joseph P Gaspar, Redona Methasani, and Maurice E Schweitzer. Emotional intelligence and deception: A theoretical model and propositions. *Journal of Business Ethics*, pp. 1–18, 2022.

Goren Gordon, Samuel Spaulding, Jacqueline Kory Westlund, Jin Joo Lee, Luke Plummer, Marayna Martinez, Madhurima Das, and Cynthia Breazeal. Affective personalization of a social robot tutor for children's second language skills. In *Proceedings of the AAAI conference on artificial intelligence*, volume 30, 2016.

Pär Anders Granhag and Maria Hartwig. A new theoretical perspective on deception detection: On the psychology of instrumental mind-reading. *Psychology, Crime & Law*, 14(3):189–200, 2008.

Viresh Gupta, Mohit Agarwal, Manik Arora, Tanmoy Chakraborty, Richa Singh, and Mayank Vatsa. Bag-of-lies: A multimodal dataset for deception detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pp. 0–0, 2019.

Maria Hartwig and Charles F Bond Jr. Lie detection from multiple cues: A meta-analysis. *Applied Cognitive Psychology*, 28(5):661–676, 2014.

Julia Bell Hirschberg, Stefan Benus, Jason M Brenier, Frank Enos, Sarah Friedman, Sarah Gilman, Cynthia Girand, Martin Graciarena, Andreas Kathol, Laura Michaelis, et al. Distinguishing deceptive from non-deceptive speech. 2005.

David M Howard and Christin Kirchhübel. Acoustic correlates of deceptive speech–an exploratory study. In *Engineering Psychology and Cognitive Ergonomics: 9th International Conference, EPCE 2011, Held as Part of HCI International 2011, Orlando, FL, USA, July 9-14, 2011. Proceedings 9*, pp. 28–37. Springer, 2011.

Wei-Ning Hsu, Benjamin Bolte, Yao-Hung Hubert Tsai, Kushal Lakhotia, Ruslan Salakhutdinov, and Abdelrahman Mohamed. Hubert: Self-supervised speech representation learning by masked prediction of hidden units. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 29:3451–3460, 2021.

David J Hughes, Ioannis K Kratsiotis, Karen Niven, and David Holman. Personality traits and emotion regulation: A targeted review and recommendations. *Emotion*, 20(1):63, 2020.

Carolyn M Hurley and Mark G Frank. Executing facial control during deception situations. *Journal of Nonverbal Behavior*, 35:119–131, 2011.

Sharon Jakobwitz and Vincent Egan. The dark triad and normal personality traits. *Personality and Individual differences*, 40(2):331–339, 2006.

Davis E King. Dlib-ml: A machine learning toolkit. *The Journal of Machine Learning Research*, 10: 1755–1758, 2009.

Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

Gangeshwar Krishnamurthy, Navonil Majumder, Soujanya Poria, and Erik Cambria. A deep learning approach for multimodal deception detection. In *International Conference on Computational Linguistics and Intelligent Text Processing*, pp. 87–96. Springer, 2018.

Sarah I Levitan, Guzhen An, Mandi Wang, Gideon Mendels, Julia Hirschberg, Michelle Levine, and Andrew Rosenberg. Cross-cultural production and detection of deception from speech. In *Proceedings of the 2015 ACM on workshop on multimodal deception detection*, pp. 1–8, 2015.

Shan Li and Weihong Deng. Deep facial expression recognition: A survey. *IEEE transactions on affective computing*, 13(3):1195–1215, 2020.

Yang Li, Amirmohammad Kazemeini, Yash Mehta, and Erik Cambria. Multitask learning for emotion and personality traits detection. *Neurocomputing*, 493:340–350, 2022.

RE Lubow and Ofer Fein. Pupillary size in response to a visual guilty knowledge test: New technique for the detection of deception. *Journal of Experimental Psychology: Applied*, 2(2):164, 1996.

Navonil Majumder, Soujanya Poria, Alexander Gelbukh, and Erik Cambria. Deep learning-based document modeling for personality detection from text. *IEEE Intelligent Systems*, 32(2):74–79, 2017.

Erik Marchi, Björn Schuller, Simon Baron-Cohen, Amandine Lassalle, Helen O'Reilly, Delia Pigat, Ofer Golan, S Friedenson, Shahar Tal, S Bolte, et al. Voice emotion games: Language and emotion in the voice of children with autism spectrum conditio. In *Proceedings of the 3rd International Workshop on Intelligent Digital Games for Empowerment and Inclusion (IDGEI 2015) as part of the 20th ACM International Conference on Intelligent User Interfaces, IUI 2015*, pp. 9–pages, 2015.

Leena Mathur and Maja J Matarić. Introducing representations of facial affect in automated multimodal deception detection. In *Proceedings of the 2020 International Conference on Multimodal Interaction*, pp. 305–314, 2020.

Kyrii Minkov, Stefanos Zafeiriou, and Maja Pantic. A comparison of different features for automatic eye blinking detection with an application to analysis of deceptive behavior. In *2012 5th International Symposium on Communications, Control and Signal Processing*, pp. 1–4. IEEE, 2012.

Matthew L Newman, James W Pennebaker, Diane S Berry, and Jane M Richards. Lying words: Predicting deception from linguistic styles. *Personality and social psychology bulletin*, 29(5): 665–675, 2003.

Michel Owayjan, Ahmad Kashour, Nancy Al Haddad, Mohamad Fadel, and Ghinwa Al Souki. The design and development of a lie detection system using facial micro-expressions. In *2012 2nd international conference on advances in computational tools for engineering applications (ACTEA)*, pp. 33–38. IEEE, 2012.

Verónica Pérez-Rosas, Rada Mihalcea, Alexis Narvaez, and Mihai Burzo. A multimodal dataset for deception detection. In *LREC*, pp. 3118–3122, 2014.

Verónica Pérez-Rosas, Mohamed Abouelenien, Rada Mihalcea, Yao Xiao, CJ Linton, and Mihai Burzo. Verbal and nonverbal clues for real-life deception detection. In *Proceedings of the 2015 conference on empirical methods in natural language processing*, pp. 2336–2346, 2015.

Ana-Catarina Pinho-Gomes, Jessica Gong, Katie Harris, Mark Woodward, and Cheryl Carcel. Dementia clinical trials over the past decade: are women fairly represented? *BMJ Neurology Open*, 4(2), 2022.

Stephen Porter, Leanne ten Brinke, Alysha Baker, and Brendan Wallace. Would i lie to you?"leakage" in deceptive facial expressions relates to psychopathy and emotional intelligence. *Personality and Individual Differences*, 51(2):133–137, 2011.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pp. 8748–8763. PMLR, 2021.

Bashar A Rajoub and Reyer Zwiggelaar. Thermal facial analysis for deception detection. *IEEE transactions on information forensics and security*, 9(6):1015–1023, 2014.

Nerella V Ramanaiah, Anupama Byravan, and Fred RJ Detwiler. Revised neo personality inventory profiles of machiavellian and non-machiavellian people. *Psychological Reports*, 75(2):937–938, 1994.

Zhancheng Ren, Qiang Shen, Xiaolei Diao, and Hao Xu. A sentiment-aware deep learning approach for personality detection from text. *Information Processing & Management*, 58(3):102532, 2021.

Patricia Rockwell, David B Buller, and Judee K Burgoon. The voice of deceit: Refining and expanding vocal cues to deception. *Communication Research Reports*, 14(4):451–459, 1997.

Justyna Sarzyńska, Marcel Falkiewicz, Monika Riegel, Justyna Babula, Daniel S Margulies, Edward Nęcka, Anna Grabowska, and Iwona Szatkowska. More intelligent extraverts are more likely to deceive. *PloS one*, 12(4):e0176591, 2017.

M Umut Şen, Veronica Perez-Rosas, Berrin Yanikoglu, Mohamed Abouelenien, Mihai Burzo, and Rada Mihalcea. Multimodal deception detection using real-life trial data. *IEEE Transactions on Affective Computing*, 13(1):306–319, 2020.

Felix Soldner, Verónica Pérez-Rosas, and Rada Mihalcea. Box of lies: Multimodal deception detection in dialogues. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pp. 1768–1777, 2019.

Jeremy Speth, Nathan Vance, Adam Czajka, Kevin W Bowyer, Diane Wright, and Patrick Flynn. Deception detection and remote physiological monitoring: A dataset and baseline experimental results. In *2021 IEEE International Joint Conference on Biometrics (IJCB)*, pp. 1–8. IEEE, 2021.

Siegfried Ludwig Sporer and Barbara Schwandt. Paraverbal indicators of deception: A meta-analytic synthesis. *Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition*, 20(4):421–446, 2006.

Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: a simple way to prevent neural networks from overfitting. *The journal of machine learning research*, 15(1):1929–1958, 2014.

Aldert Vrij. *Detecting lies and deceit: Pitfalls and opportunities*. John Wiley & Sons, 2008.

Aiyuan Yang, Bin Xiao, Bingning Wang, Borong Zhang, Ce Bian, Chao Yin, Chenxu Lv, Da Pan, Dian Wang, Dong Yan, et al. Baichuan 2: Open large-scale language models. *arXiv preprint arXiv:2309.10305*, 2023.

Bo Zhang, Yi Ming Li, Jian Li, Jing Luo, Yonghao Ye, Lu Yin, Zhuosheng Chen, Christopher J Soto, and Oliver P John. The big five inventory–2 in china: A comprehensive psychometric evaluation in four diverse samples. *Assessment*, 29(6):1262–1284, 2022.

Le Zhang, Songyou Peng, and Stefan Winkler. Persemon: a deep network for joint analysis of apparent personality, emotion and their relationship. *IEEE Transactions on Affective Computing*, 13(1):298–305, 2019.

Lina Zhou, Judee K Burgoon, Jay F Nunamaker, and Doug Twitchell. Automating linguistics-based cues for detecting deception in text-based asynchronous computer-mediated communications. *Group decision and negotiation*, 13:81–106, 2004.

Mircea Zloteanu, Peter Bull, Eva G Krumhuber, and Daniel C Richardson. Veracity judgement, not accuracy: Reconsidering the role of facial expressions, empathy, and emotion recognition training on deception detection. *Quarterly Journal of Experimental Psychology*, 74(5):910–927, 2021.

Miron Zuckerman, Bella M DePaulo, and Robert Rosenthal. Verbal and nonverbal communication of deception. In *Advances in experimental social psychology*, volume 14, pp. 1–59. Elsevier, 1981.

, , and . . , 24(7):551–554, 2010.

A Appendix

A.1 Big Five Personality Inventory Second Edition (BFI-2)

Below are some descriptions of personal characteristics, some may or may not apply to you. Please fill in the corresponding number on the horizontal line before each sentence below to indicate whether you agree or disagree with this description.

1. Outgoing personality, enjoys socializing
2. Soft hearted and compassionate
3. Lack of organization
4. Calm and adept at handling pressure
5. Not very interested in art
6. Strong and confident personality, daring to express one's own opinions
7. Humble and respectful towards others
8. Relatively lazy
9. Being able to maintain a positive attitude even after experiencing setbacks
10. Interested in many different things
11. I rarely feel excited or particularly want to do anything
12. Often picking on others' faults
13. Reliable and reliable
14. Irregular mood and frequent emotional fluctuations
15. Skilled in creativity and able to find smart ways to do things
16. Relatively quiet
17. Lack of empathy towards others
18. Work in a planned and organized manner
19. Easy to get nervous
20. Enthusiastic with art, music, or literature
21. Often in a dominant position, like a leader
22. Often having disagreements with others
23. It's difficult to start taking action to complete a task

24. Feeling secure and satisfied with oneself
25. Disliking discussions with strong knowledge or philosophy
26. Not as energetic as others
27. Be magnanimous and magnanimous
28. Sometimes I lack a sense of responsibility
29. Emotionally stable and less likely to get angry
30. Almost no creativity
31. Sometimes shy and introverted
32. Helpful and selfless towards others
33. Habit keeps things tidy and orderly
34. Often worried and worried about many things
35. Valuing Art and Aesthetics
36. Feeling difficult to influence others
37. Sometimes being rude to people
38. Efficiency, starting and ending with work
39. Often feeling sad
40. Deep thinking
41. Full of energy
42. Do not trust others and doubt their intentions
43. Reliable, always trustworthy to others
44. Able to control one's emotions
45. Lack of imagination
46. Loud and talkative
47. Sometimes cold and indifferent to others
48. It's messy and doesn't like to tidy up
49. Rarely feel anxious or afraid
50. Feeling bored with poetry and drama
51. I prefer to have others take the lead and take responsibility
52. Humility and courtesy towards others
53. Have perseverance and be able to persist in completing tasks
54. Often feeling depressed and unhappy
55. Not very interested in abstract concepts and ideas
56. Full of enthusiasm
57. Think about people in the best possible way
58. Sometimes they may engage in irresponsible behavior
59. Emotions are variable and prone to anger
60. Creative and able to come up with new ideas

A.2 Emotional Sacle

After watching the video, you need to rate the following emotions: sadness, relaxation, happiness, surprise, fear, anger, disgust, and neutral. Mark to what extent you feel it appropriately expresses your feelings, with intensity ranging from 1 to 5, where 1 is the least intense and 5 is the strongest.

Video Number	Sadness	Relax	Happiness	Surprise	Fear	Angry	Disgust	Neutral
1								
2								
3								
4								
5								
6								
7								
8								
9								
10								
11								
12								
13								
14								
15								
16								

A.3 Interview Questions

1. What color do you like the most? Why?
2. Where is your hometown? Please briefly introduce it.
3. Do you have any hobbies?
4. Have you traveled in the past year?
5. How do you like Beijing?
6. What is your happiest experience?
7. What is your favorite food?
8. What is your personality like?
9. What is your biggest weakness?
10. What is your greatest strength?
11. What do you usually do to relax?
12. Which exercise or sport do you like?
13. Briefly introduce your family members.
14. Who is the person you have the greatest influence on you?
15. Do you have any special places or tourist destinations you want to go to?
16. Who is your favorite celebrity or great person?
17. What is your opinion on the words "neijuan" and "tangping"?
18. What is your favorite literary and artistic work?
19. Have you ever received any rewards or honors in school or at work?
20. What was your most unforgettable experience in the past year?
21. Have you participated in any major event?
22. Have you ever cheated in school or work?
23. Have you concealed a fact to your family or friends in the past year?
24. Have you ever lied to avoid responsibility?