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Psychological Effect Computation of Courtroom Arguments: A Deep Learning Approach of EEG Signal Data

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Abstract Previous studies have shown that the attorney's speeches can exert significant impacts on the cognition and judgment of the jury in court arguments. However, the psychological effects induced by these speeches are intricately tied to subconscious brain states, making them challenging to accurately and comprehensively describe through subjective self-reports. This study aims to explore a neural reaction observation method for psychological effect analysis of the attorney's speeches in courtroom scenarios. We utilized a corpus of courtroom arguments from legal movies and television series as source material. Participants' psychological responses to these speeches were monitored using wearable electroencephalography (EEG) devices. Building upon this data, we employed a deep learning model based on Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to compute attention intensity, cognitive load, and emotional changes. Our test results demonstrate that this approach enables continuous and dynamic computation within courtroom argument contexts, providing a more accurate assessment of attorneys' language skills.

Keywords: Courtroom argument, attorney' Speech, psychological effect, EEG, CNN-LSTM.

1. Introduction

Courtroom argument is the vital part of the trial process, its language skills have important impacts on the cognition and adjudication of the trialed case [1-4], and have attracted the common interest and attention as an interdisciplinary research domain of law, linguistics, and psychology [5, 6]. Crucially, the attorneys need to utilize various logic and emotional expression skills according to the designed defense strategies, to guide the cognitions of the trial personnel and persuade them to make the judgmental

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decisions in favor of their clients [7-10]. Besides, the criterion as to whether justice is fulfilled had to consider the usual judgements of ordinary people, especially in most western countries which have a jury system. The jury represents the consensus of the society or a local social community, not the thinking of legal professionals. Therefore, the courtroom arguments should be presented and accepted in the light of the cognition and judgment of the public. Conley et al. analyzed the impact of changes in the presentational style of courtroom language on the decision makers [7]. Hahn and Clayton evaluated the effect of attorneys' narrative style and gender on decisions of the jury [8]. They all concluded that the excellent language skills of the attorneys play an important role subtly in striving for acquittals for their clients.

As for the language skills in courtroom arguments, the language act theory and pragmatic studies regard it as an issue of linguistic psychological effects, which are caused by the following features embedded in the argument speeches: legal compliance, logical validity, and psychological effects [9-11]. Hu expounded the legal compliance from five perspectives of jurisprudential norms, discourse power norms, procedural norms, evidentiary norms, and debating norms [9]. Shalmanova and Shumov made a further study on the precision problem of court language [10]. Based on the corpus analysis of approximately 1000 sentences extracted from the case records of the US Supreme Court, Liu investigated the lawyers' arguments from the perspective of linguistic communication dynamics, and revealed the language logic and the characteristics of the emotional expression [11]. Yu analyzed the factors affecting the acceptance of courtroom arguments from the viewpoint of legal thinking and logical methodology, and emphasized the roles of situational cognition and persuasive utility under the above specific contexts [12]. This utility can be understood as the resulting valence of psychological effects for the trial personnel or the public.

The psychological effects caused by languages usually include cognitive and emotional aspects dominated by human brain mechanism [13-16], which have mutual influence and involve a series of descriptive indicators. However, this study mainly focuses on the three indicators of attention intensity, cognitive load, and emotional change, which are of great significance to the analysis of language skills under the scenarios of courtroom arguments. Attention intensity usually reflects how much attention is paid to the speeches presented by the arguer, cognitive load represents how easy it is for the listener to understand what is being said by the arguer, and emotional change indicates how emotionally affected the listener is by the arguer's speeches [17, 18]. Nowadays, a lot of computational methods have been presented for psychological effect analysis of human speeches [20-22]. Nevertheless, the induced psychological effects by speeches are closely pertinent to the brain's subconscious perception, which are difficult to be described and expressed in subjective narration at the state of consciousness [25, 26]. In recent years, the development of experimental observation techniques in neuroscience such as electroencephalography (EEG) has made it possible to observe the brain neural activity in the subconscious or even unconscious states, thereby EEG data has been applied to emotion recognition and affective computation for achieving more accurate results [25-28]. Different from the above existing researches, this study aims to explore the method for continuous and dynamic psychological computation of attention intensity, cognitive load, and emotional changes induced by the attorney's speeches based on EEG signal data. The above psychological effects and neural mechanism are also the great concerned issue in the feild of Neurolaw [29].

2. Data Acquisition and Preprocessing

In the experiment, a total of 22 qualified subjects (10 males and 12 females) aged between 18 and 55 were selected as members of a mock jury or public representatives. Among them, 12 were undergraduate and graduate students while the remaining 10 were teachers and employees of government agencies and companies. Further, three had a background in legal profession, 8 in humanities and social sciences, 6 in engineering and technology, and 5 in mathematics, physics, and medical science. Prior to the experiment, each subject was fully informed on the experimental purpose, process, and potential impacts on human body in accordance with the ethical norms, and signed an informed consent form.

In order to avoid the influence of the subjects' preconceptions about the case and characters, the courtroom argument scenarios extracted from the famous movie "And Justice for All" and the television series "American Crime Story: The People v. O.J. Simpson" were used as the test materials in the study, as shown in Fig. 1.

Fig. 1. The courtroom argument scenarios extracted from the movie "And Justice for All" (left), and the television series "American Crime Story: The People v. O.J. Simpson" (right)

The experiment used a specifically designed computer control system for EEG testing, which can collect the data from EEG device according to the following experimental procedure and paradigm.

Stage 1: Preparation for testing. Put on the electrode cap for the subject and debug the EEG device; prepare the subjects in the resting and calm state while the control computer sends the instruction to begin the test.

Stage 2: Resting-state data acquisition. Start the EEG to record the resting-state brain electrical signals in the first 30s, and then to transmit the data to the control computer in which a special software reads and stores them in the database.

Stage 3: Synchronous data acquisition. The control computer issues the EEG testing instructions, which is then conditioned by the synchronous measurement and control unit. The output signals are sent out and the variation of the EEG signal is recorded and transmitted to the control computer for storage. In the meanwhile, the psychological effects of the attorneys' speeches are evaluated by the subjects with a group of rotary mechanical levers. Based on the position changes, the levers can convert the psychological effects into the score values between intervals of attention intensity [0,5], cognitive load [0,5], and emotional change [-5,5], and the results are stored in the database.

Stage 4: Test completion. The control computer sends out instructions to complete the test and to restore the device to its initial state.

The study adopted the international standard of 10-20 double-lead 8-channel EEG signal acquisition, in which the electrode distribution of the 8 channels was as follows: C1: Fp1-T3, C2: Fp2-T4, C3: T3-O1, C4: T4-O2, C5: Fp1-C3, C6: Fp2-C4, C7: C3-O1, C8: C4-O2. During the playback of the test materials, we collected 18 paragraphs of EEG signals with total 26 minutes 20 seconds containing only the attorneys' speeches through computer synchronous control. For example, the structure of EEG raw data for one scenario of the attorneys' speeches shows as in Table 1.

Table 1. The structure of EEG raw data for one scenario of the attorneys' speeches

scenario	mi	se	c1	c2	c3	c4	c5	c6	c7	c8	bs
	1.391	83.438	-19.386	-31.445	-17.582	-31.784	-14.201	-26.374	-11.496	-26.036	-738.123
	1.391	83.445	-12.172	-24.345	5.748	5.748	10.144	5.748	9.467	8.791	-738.123
	1.391	83.453	-13.863	1.014	-16.230	-10.144	-7.777	-5.410	-24.683	-.338	-738.123
	1.391	83.461	-32.347	-14.201	-25.359	1.014	-18.597	-1.352	-.676	5.072	-738.123
	1.391	83.469	-24.007	-7.439	-.338	10.482	-4.396	7.101	6.762	27.050	-738.123
	1.391	83.477	-23.105	-1.014	-11.496	-3.719	-13.525	-4.734	-2.029	-2.367	-738.123
	1.391	83.484	-26.712	-15.216	-6.086	-.3380	-9.129	-2.029	.338	-7.777	-738.123
	1.392	83.492	-24.007	.338	-10.82	-12.172	-13.863	-4.057	-12.511	1.352	-738.123
	…	…	…	…	…	…	…	…	…	…	…

The EGG signals are collected once per 8ms and therefore composing a time series. In the data processing, the study first filters out the EEG data before and after 2s of the changing process of each lever, because those data may be affected by manual operations and could not accurately reflect the psychological changes of the subjects. In addition, a cubic spline interpolation method is used to interpolate the score values of psychological effects to form the time series synchronously with EEG data for machine learning.

The EEG signals can be processed by means of wavelet decomposition and reconstruction to yield typical brain wave frequencies such as δ (0.5-3Hz), θ (4-7Hz), α (8-13Hz), β (14-30Hz), and γ (>30Hz). Among them, the θ and α waves are mostly linked to the brain's subconscious and unconscious states. In order to get more accurate computation results by machine learning, the study divides the signals into the following nine subdivided bands: δ (0.5-3Hz), θ (4-7Hz), low α (8-10Hz), high α (11-13Hz), low β (14-15Hz), midrange β (16-20Hz), high β (21-30Hz), low γ (31-40Hz), and midrange γ (41-50Hz) , and pre-processes the EEG signals by filtering and wavelet transform to obtain the values of each subdivided band for the subsequent machine learning.

3. Machine Learning Method

3.1. CNN-LSTM Model

The CNN-LSTM model combines with the advantages of LSTM (Long Short-Term Memory) model and CNN (Convolutional Neural Networks) model, which has been successfully applied to the emotion recognition from EEG signals in recent years [30]. Therefore, we design the CNN-LSTM model architecture and employ it for the correlation assessment between EGG signals and indicators of attention intensity, cognitive load, and emotional changes. We mainly focus on the use of LSTM since it has several advantages on dealing with the problem in the study. Firstly, LSTM has a chain-like structure which makes it suitable for time series analysis. Secondly, as a non-linear model, LSTM can be used as a complex non-linear unit for constructing larger deep neural networks. Thirdly, LSTM can remember information for extended periods of time, helping it to handle long-term dependencies.

In the proposed CNN-LSTM model architecture, CNN is used for further feature extraction, and LSTM is applied to exploit temporal relationships in the data. These two sections are linked together in order to perform higher accuracy. Specifically, 1D Convolutional Neural Network is adopted as a feature extractor and data encoder, providing more features for the LSTM to train and calculate. Compared with traditional fully-connected neural networks, 1D-CNNs can better handle local relationships in sequential data, and therefore perform better in tasks such as speech recognition, natural language processing, and time series prediction. It can automatically extract important features from the data, thus reducing the workload of manual feature extraction, while providing better generalization performance.

A model based on LSTM is designed to control the accumulation rate of information by introducing gating mechanisms as shown in Fig. 2, including selectively adding new information and selectively forgetting previously accumulated information, thereby improving the long-range dependency problem of recurrent neural networks (RNNs) and alleviating the gradient disappearance problem during the training of long sequences.

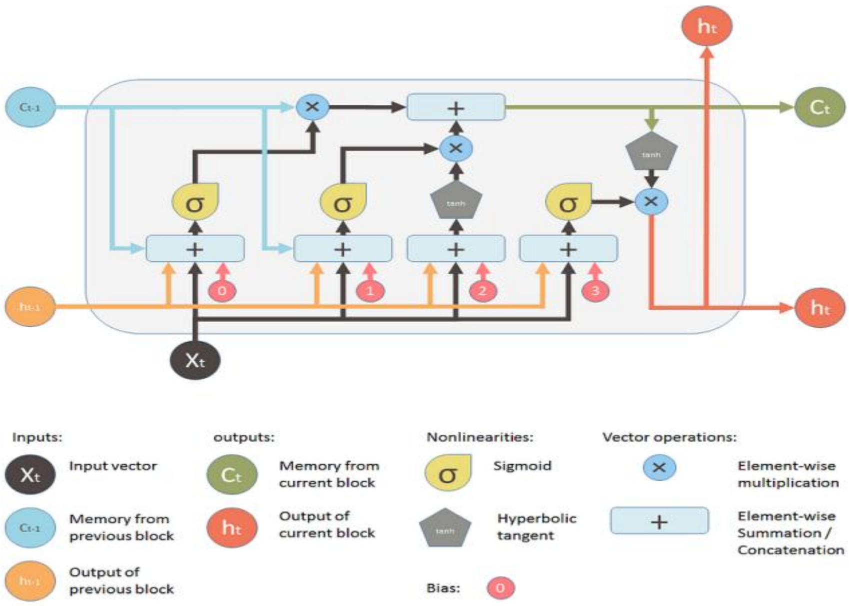

Fig. 2. LSTM built block

The first step of the LSTM is to decide what information to discard or keep. This decision is made by a "forget gate" which selectively forgets by sigmoid function.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

The second step which consists two parts are taken to update the cells status. The "input gate" uses sigmoid to determine which values to update and tanh to generate new candidates. The sigmoid output is then multiplied by the tanh output candidates, i.e., the sigmoid output determines which of the tanh output values are important to keep.

$$i_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\widetilde{C_t} = tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{3}$$

Finally, the output values are calculated by output cell state. The output is first obtained through the sigmoid layer, and then the new memory cell state obtained in the previous stage is deflated using tanh and then multiplied pair by pair with the output obtained from sigmoid to determine the information which the hidden state should carry. The new hidden state is used as the current output, thereby, the new information is passed to the next time step.

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t} \tag{4}$$

The model consists two CNN layers, a one-layer LSTM network and a full connected layer as shown in Fig. 3. A dam optimizer together with a learning rate of 0.001 which would be divided by 2 in every 15 epochs is applied. The architecture is programmed in Pytorch. All the figures are trained in a batch size of 2.

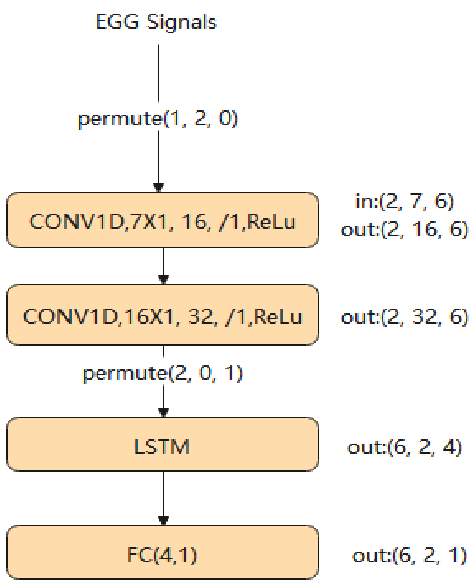

Fig. 3. Model architecture

3.2. Training and Evaluation

The model for three different output features, namely attention intensity, cognitive load, and emotional change, are trained respectively. The model architecture and hyperparameters for these features are the same. Because the induced psychological effects by speeches are closely related to the perception at the brain's subconscious states, which can't be described accurately and comprehensively through a subjective self-report way. However, the psychological effects under brain's subconscious states and conscious states have relationships in different band waves of EEG signals for the same subject [24], and existing studies indicated that PSD (Power Spectral Density) parameters of the EEG signals have good performance in emotion recognition [24, 27, 28]. Therefore, we use the following adjusted formula to calculate the full psychological effects, and take which as the target values for machine learning.

$$P(i) = P_e(i)(1 + PSD_m/PSD_e), i = 1,2,3 \tag{5}$$

where, P_e(i) stands for the explicit part of psychological effects that can be evaluated by the subjects under conscious states in Step 3 of the experimental procedure, while PSD_m and PSD_e are the power spectral densities of band 0.5-7 Hz (δ and θ waves) and band 8-50 Hz (α, β, low γ, and midrange γ waves) respectively for the same subject. Using the adjusted target values for machine learning can better consider the subconscious psychological effects [24].

The study first numbers the data sequentially, and then randomly divides these data into three parts, namely learning data set, validation data set and test data set, with a proportion of 8: 1: 1, and RobustScaler is used for the normalization of the input data so as to reduce the impact of outliers. The training process of the model architecture is as follows. First, EEG Signals are permuted to the size of (2, 7, 6) and sent into a 2-layer CONV1D network to extract features from the raw signals. The first CONV1D layer has 16 1x1 kernels and the stride of convolution kernels is 1. The second one has 32 kernels, with the same size and stride. Each CONV1D layer is followed with a ReLU unit which can introduce non-linearity to the proposed model. The output features, after passing through the CONV1D layers, are then fed into the LSTM layers, which have the capability to circumvent the long-term dependency problem inherent in standard RNNs. Upon passing through the LSTM layers, the output features are subsequently directed into a FC layer. Ultimately, a softmax output layer is appended to the proposed model to facilitate final recognition.

The learning performances are evaluated by a MAPE (Mean Absolute Percentage Error) curve. Equation (6) shows the calculation of MAPE, where, n is the total number of predict values, A_t is the actual value at time t and C_t is the calculated value.

$$\mathrm{MAPE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{t}=1}^{\mathrm{n}} | \frac{\mathrm{A_t}-\mathrm{C_t}}{\mathrm{A_t}} \times 100\% | \tag{6}$$

The CNN-LSTM model performances of attention intensity, cognitive load, and emotional change are shown in Fig. 4, Fig. 5, and Fig. 6 respectively.

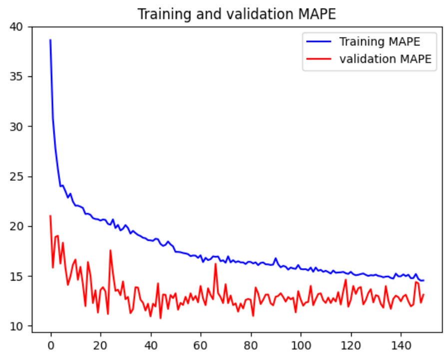

Fig. 4. MAPE curve of attention intensity

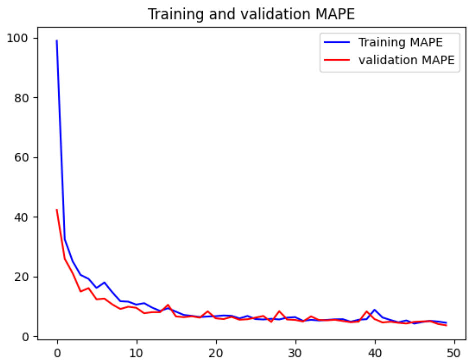

Fig. 5. MAPE curve of cognitive load

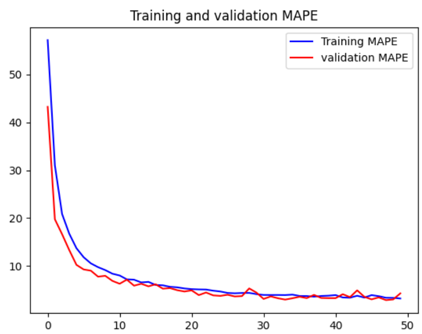

Fig. 6. MAPE curve of emotional change

The final trained MAPEs of CNN-LSTM model, CNN model, and LSTM model are shown contrastively in Table 2.

Table 2. Final trained MAPEs of different models

Model Name	MAPE		
	Attention intensity	Cognitive load	Emotional changes
CNN-LSTM	7.802%	3.188%	14.544%
CNN	22.672%	9.387%	41.053%
LSTM	9.411%	4.123%	20.134%

As seen from Table 2, the CNN-LSTM model can achieve more higher accuracy than a single CNN model or LSTM model, which provides an appropriate and valid approach for the continuous and dynamic computation of psychological effects from EEG data.

4. Psychological Effect Analysis

The US courts deal with cases mostly in adversarial proceedings, for which the main idea is that the court relies on the evidence presented by the litigation parties to develop the judgement. The main speech roles in the courtroom include the judge, the prosecutor, the attorneys, the witnesses, and the defendant. In criminal cases, the prosecutor and the attorneys participate in the proceedings as agents for the state and the defendant, respectively. In the common law jury trial, the jurors act as the fact finders and decide whether the defendant is guilty or not. If found guilty, further sentencing is to be made by the judge who is required to assume the role of presiding over the entire case.

In order to illustrate how the attorneys' linguistic skills would affect the psychology of the jury, this study takes the famous Simpson case as example. Two audio clips are extracted from the attorneys' speeches in the television series of "American Crime Story: The people v. O.J. Simpson", and are used as the source material for analysis. The psychological effects of attention intensity, cognitive load, and emotion changes are computed by the trained CNN-LSTM model. In order to facilitate comparison, the average values of all subjects are uniformly converted into the range between interval [-1,1], as shown in Fig. 7 and Fig. 8.

Segment 1: The interrogation conversation between the defense attorney F. Lee Bailey and the prosecuting witness Detective Mark Fuhrman regarding whether he had utilized the term "nigger."

The attorney's speeches: I will ask a different question. In describing people, Detective Fuhrman, do you use the word "Nigger"? Detective Fuhrman, have you ever used the word "nigger" when addressing someone? // Have you ever used the word "Nigger" in the past ten years? // You mean if you called someone a nigger, you have forgotten it? // Let me put it simply. Are you saying, under oath, that you have not addressed any black person as a nigger or spoken about black people as niggers in the past ten years, Detective Fuhrman? // So, then anyone who comes to this court and quotes you as using that word in dealing with African-Americans would be a liar. Would they not, Detective Fuhrman? // All of them, correct? // Thank you, no further questions.

Psychological effects: As shown in Fig. 7.

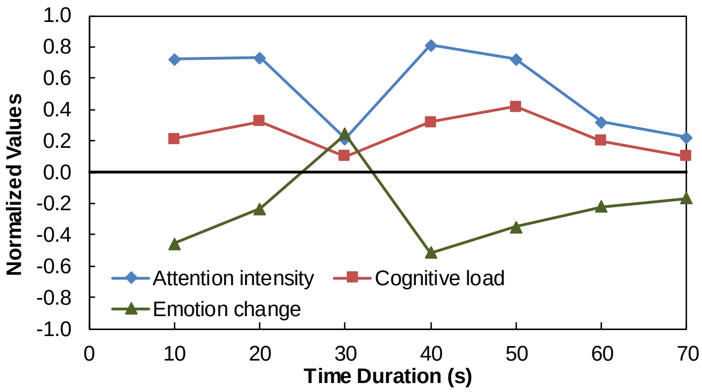

Fig. 7. Psychological effects of the attorney's speeches in Segment 1

Language skills: The attorney threw out four consecutive rhetorical questions to induce the witness to make an affirmative and clear statement that he never used the word "nigger". The purpose of these questions was not to create confusion, but to set the stage for subsequent testimony that Fuhrman frequently used insulting words such as "nigger," thereby arousing the jury's or the public's distrust on him and rendering his testimony ineffective. As shown in Fig. 7, the attention density of the mock jury (or the public members) was at a high level, the cognitive load was moderate, and the emotion change varied in the negative region, indicating that the attorney's questions triggered a high degree of attention and formed negative perceptions with relative ease. In short, his linguistic skills produced highly desirable results.

Segment 2: The defense attorney Barry Scheck questioned the criminal examination expert Dennis Fung on the key evidence of blood and hair.

The Attorney's Speeches: Mr. Fung, you received from Detective Lange, the blood sample taken from Mr. Simpson, correct? // And where did you take possession of that blood sample? // Well, maybe I can help. The blood was handed to you at the Rockingham scene while you were examining that scene, correct? // So, Mr. Simpson's blood was literally handed to you by LAPD at the very location where you found evidence of his blood on the carpet in the driveway, in his socks? // This might explain a huge unanswered question in this case. Are you aware, sir, that 1.9 milliliters or one quarter of the blood collected from Mr. Simpson is missing?! // Mr. Fung, when did you realize that the blanket covering Nicole Brown's body was actually from inside her own residence? // Would you agree, sir, that a blanket taken from inside her residence placed by law enforcement over her dead body could be thought of as a contamination of that scene? // And that if Mr. Simpson had been in that home previously, sitting or lying on that blanket, his hairs could be on that blanket? Would be on that blanket? And thus, would have been in the crime scene? // That is a terrible mistake for a criminalist to make. Isn't it? // Mr. Fung, have you made some bad choices in this case? // No further questions.

Psychological effects: As shown in Fig. 8.

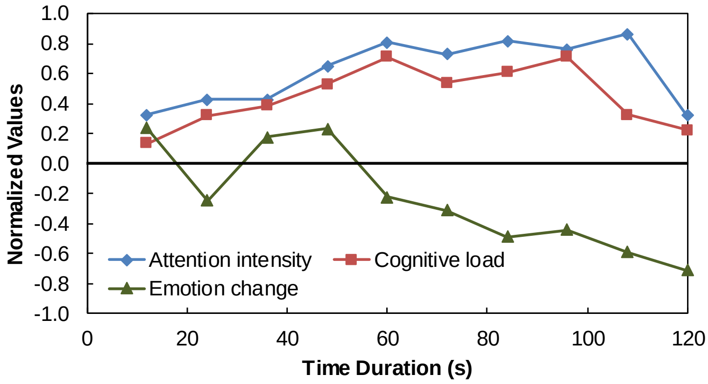

Fig. 8. Psychological effects of the attorney's speeches in Segment 2

Language skills: The attorney used a barrage of questions that caused the witness to gradually begin to doubt the legitimacy of the evidence. Stammering and ambiguous in his answers, the expert witness not only was interrupted several times by the attorney, but also agreed that "that is a terrible mistake for a criminalist to make." Using quick and frequent questioning, the attorney effectively consolidated his dominant voice and controlled the direction of the whole conversation, making the jury (or the public) naturally doubt the credibility of the procurators' key evidences. According to Figure 8, the attention density of the mock jury (or the public members) was always at a high level, indicating that the attorney's questions had triggered a high level of attention. The cognitive load level was also high, suggesting that the questions had prompted a deep thinking. The overall rapid reduction of emotion changes into the negative region reflected that the jurors (or the public) had developed strong doubts and dissatisfaction. In short, the attorney's language skills were again highly successful in producing the desired effects.

5. Summary and Discussion

The study of courtroom arguments is becoming a hot topic in the multidisciplinary fields. It is of important significance for the in-depth analysis of the jurors' (or the publics') cognitions and affecting factors, and also for improving the language skills of the litigation parties and maintaining the impartiality in legal adjudication for the society.

Especially, the attorney's speeches in court arguments can produce subtle cognitive and emotional effects on the jurors, and significantly affect their judgment. Those psychological effects are closely related to the subconscious perception of human brains, and difficult to be reflected in a subjective self-report way. This study explored the psychological computation method based on EEG signal data for coping with the problem. A valid deep learning approach with CNN-LSTM model architecture was presented for evaluating the full psychological effects induced by attorney's speeches, in terms of attention density, cognitive load, and emotion changes.

In real trials, the courtroom arguments are conducted in the form of dialogues between two or more parties with complex contexts and involving multi-faceted expertise. Therefore, further exploration is needed in the accurate extraction of EEG signals and on the cognitive discrepancies between the jury or the public members with different genders and professional backgrounds. In addition, the neural mechanisms underlying these psychological effects have yet to be systematically investigated in conjunction with various neuro-experimental equipment such as functional magnetic resonance imaging (fMRI) and event-related potentials (ERPs). Besides, the main purpose of this study is to explore the valid approach to compute the above psychological effects, and the complicated factors causing those effects are not thoroughly considered.

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