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RESEARCH ARTICLE

Classification and Prediction of Driver's Mental Workload Based on Long Time Sequences and Multiple Physiological Factors

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ABSTRACT The driver's mental workload is closely related to driving safety. However, how to analyze the driver's mental workload in a reasonable and correct manner remains an open question. As an important factor to evaluate mental workload, changes in physiology encounter two clear problems: (1) Physiological factor contains multi-characteristic indicators, there is a lack of reasonable means for synchronizing multi-dimensional tabular data, and the limits of tabular data processing in the evaluation of mental workload have a significant impact on the evaluation results. (2) The physiological data obtained during the driving process are of the time-series variety. The correlation of numerous indicators must be considered in time-series data correlation analysis. Mental workload should be the result of multiple indicators interacting over time, rather than a single instant. In this regard, we propose a model, that is the long time sequences and multiple physiological factors(LTS-MPF), for classifying and predicting multiple physiological changes in the time series. In contrast to previous methods of processing data in a single instant, LTS-MPF can directly analyze all time-series factors that may affect the driver's mental workload during a time interval, such as Heart rate growth, Heart rate variability, and Electrodermal activity, and so on. Furthermore, LTS-MPF can predict the driver's mental workload in the next 1s as well as classify the current sequence's results. Specifically, we collect physiological data from drivers via sensors. These collected data are processed and transformed into tabular data. The table's columns represent features, while the rows represent all feature data at one moment in time. The row order also indicates the forward and backward order of the different moments. We convert each row in this table into an embedding feature and feed the entire table into our proposed LTS-MPF based on the Transformer model. The LTS-MPF achieves time series correlation while eliminating column feature series irrelevance. The experiment results reveal that LTS-MPF exceeds earlier techniques in forecasting the driver's mental workload, with an accuracy of up to 94.3%. And its accuracy in predicting mental workload in the future for one second can reach 93.5%. These findings suggest that LTS-MPF can be utilized to not only better evaluate a driver's mental workload in the present, but also in the future, providing solid data for early warning of dangerous driving behaviors and enhancing driving safety.

INDEX TERMS Driver's mental workload, physiological factor, long time sequences and multiple physiological factors, tabular data, transformer model.

I. INTRODUCTION

Driver's physiological changes during the driving process show the fluctuation of their mental workload. Furthermore,

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changes in mental workload can have a direct impact on drivers' safety. Drivers may delay processing information or even fail to react in time if their mental workload is too high. When the driver's mental load is too low, drivers may make mistakes due to boredom or burnout. Too high or too low mental workload also can have a negative impact on driving safety. Therefore, a proper evaluation of the mental workload of driving can be a reasonable and effective way to ensure driving safety.

Given the amount of time and effort spent on establishing methods to optimize workload, it would appear that everything related to workload and workload assessment would be well defined and acknowledged. The widely accepted definition of mental workload was proposed by Hicks in 1979 [1] as "Mental workload is a hypothetical construct that describes the extent to which the cognitive resources required to perform a task have been actively engaged by the operator". Several methods for evaluating the driver's mental workload have been developed. These methods are divided into three: (1) subjective measurement; (2) performance measurement; (3) physiological measurement [2], [3], [4], [5]. The subjective measurement is based on the driver's memory and takes the form of a questionnaire in which the driver answers questions about the driving process [6]. The subjective measurement is regarded as the most flexible and convenient technique of burden evaluation due to the ease of access to its evaluation results and the cheap cost of collection [4]. However, it does not provide a continuous form of measurement, and the results are affected by recall bias and the driver's short-term memory. After subjective measurement, answers to the questions filled out by each driver for each time interval are organized into a table. The performance measurement refers to the driver's behaviors in accomplishing a task, which is divided into two types: a direct measurement, e.g., vehicle transverse and longitudinal acceleration, speed, lane shift, distance headway, etc. [7], [8]and an indirect measurement, e.g., driver's responses to stimuli in the driving process [9], [10], [11], Regardless of the statistical method, these acquired data will eventually be stored in a table. The physiological measurement covers the quantitative measurement and visualization of physiological signals to indirectly detect a driver's mental workload. Currently, physiological measurements are divided into five main categories [12], [13], [14]: eye activity, heart activity, brain activity, muscle activity, and other related activities. We can record any type of physiological data while driving using sensors. Finally, regardless of the method used to collect data for driver mental workload evaluation, the collected data is stored in tables. Each column in this table indicates a separate factor, such as the driver's heart rate, electromyography, vehicle speed, acceleration, and so on, while each row provides a specific value of those mentioned characteristics at any given time.

We expect the collected tabular data should allow us to directly classify or predict the mental workload of drivers. Many machine learning algorithms, such as support vector machines (SVM), neural networks, random forests, and so on, were developed to address this issue [15], [16], [17]. However, these trained models usually fail to generalize effectively and have low accuracy, potentially due to changes in the data itself. Physiological data fluctuates, whereas velocity data is linear. Processing both forms of data at the same time is frequently inadvisable. For example, when just using heart rate and speed to evaluate mental workload, the same mental workload evaluation findings are produced if both speed and heart rate is the same at different times. However, the mental workload for the same heart rate that is in two processes of rising and falling should be different. This contradicting data is damaging to machine learning algorithms because it makes it difficult to converge the model, decreasing generalization. However, most of these machine learning algorithms that identify the driver's mental workload for each moment of feature data struggle to depict the driver's mental workload realistically. Because mental workload fluctuates continuously, it is not as if it was high in the last few moments and suddenly drops in the next few. As a result, the previous method of data processing may not be the best option for categorizing mental workload. In summary, we find (1) the physiological factor is a multi-characteristic indicator, and there is a lack of reasonable means for simultaneous processing of multi-dimensional tabular data, and (2) the physiological data obtained from the driving process is time-series, and correlation analysis of time-series data must take into account the correlation of multi-characteristics.

Recently, there has been much interest in data tables, which are semi-structured data with variable lengths without a fixed data model. Strategies based on the Transformer architecture have also performed well in various table inference tasks. Many works use Transformer in a BERT manner, serializing tables or rows into word sequences. That is, each moment of physiological data is treated as a word, and temporal multidimensional data as a complete sentence. However, most Transformer models require table structure linearization, or converting the row and column order into a fixed positional encoding. The before-and-after order of rows in physiological data indicates their back-and-forth relationship on time series, and they have fixed position encoding. The before-and-after order of columns, on the other hand, should be random. The previous linearized table processing introduces spurious column order bias. As a result, these models are vulnerable to column order perturbations, which can affect driver mental workload classification or prediction. In response, we propose LTS-MPF, which is based on the Transformer structure for processing physiological data for table comprehension convenience. When linearizing the acquired tabular data, irrelevance to column order perturbations will be achieved by incorporating structural deviations of the columns. LTS-MPF has the following characteristics: (1) It can better handle physiological data without the influence of column sequences on the model when constructing time series correlations. (2) It can directly deal with whole table data with good induction bias of table data, and it can more directly classify or predict the mental workload of drivers. Experiments show that LTS-MPF exceeds earlier techniques in forecasting the driver's mental workload, with an accuracy of up to 94.3%. And its accuracy in predicting mental workload in the future for one second can reach 93.5%.

All experimental results support the efficacy of LTS-MPF. The following are our contributions:

- For the first time in the processing of physiological data, we introduced a new Transformer model LTS-MPF, and used the column-independent processing approach in modeling.
- The processing of the entire table achieves physiological data processing in time series and simultaneous processing of multidimensional data. It is also more consistent with the overall use of physiological data.
- The proposed LTS-MPF is not only good for classifying drivers' mental workload, but also for predicting later moments, demonstrating its potential value.

II. RELATED WORKS

A. CLASSIFYING DRIVER MENTAL WORKLOAD USING PHYSIOLOGICAL DATA

Collecting and analyzing drivers' physiological data has become an important way to evaluate the mental workload of drivers while driving [18], [19], [20]. Their physiological changes reflect their mental workload as well. Heart rate growth (HR growth), Heart rate variability (HRV), and Electrodermal activity (EDA) are the three most commonly used physiological indicators to evaluate a driver's mental workload. The HR growth rate is determined by the driver's HR variability or the number of heartbeats per minute. HR is a vital physiological indicator of the human body [21], [22], but it differs among drivers. As a result, the HR growth rate can better capture the driver's HR variability at various points in time. HRV, which refers to how fast or slow the HR rhythm is at different times of HR, also uses HR as the basic unit. HRV is studied in driver's mental workload analysis tasks as the small rise and fall of the RR interval between linked HRs [23]. EDA, on the other hand, is an important physiological indicator. EDA is caused by the autonomic activation of skin sweat glands in response to emotional stimuli. In a state of unconscious behavior, EDA can test a driver's true psychological state [24]. After obtaining the driver's physiological data during driving, the data from the same moments will be organized together. As a result, the entire dataset will be converted into physiological data about the driver at various time intervals. The driver's mental workload analysis should then synthesize these characteristics. These organized tabular data present multidimensional, nonlinear characteristics in studies. Many studies make use of various classification algorithms, such as Neural network (NN), Support vector machines (SVM), and Random forest (RF) [16]. However, in practice, these models can frequently only model data based on multiple sets of data per moment, and they are unable to learn about the entire table of data, i.e., the ability to learn over a long time series. As a result, models based on a single point in time frequently struggle to achieve good generalizability.

B. PROCESSING AND UNDERSTANDING OF TABULAR DATA

Various tasks in machine learning are performed on long sequences of multidimensional data, so we should analyze tabular data. These tasks can be divided into table-based semantic parsing tasks, table-based automated question and answer, and table-based fact-checking [25]. The output of table-based semantic parsing is typically a semantic understanding sufficient to perform database queries on table data [26]. For instance, statistical student achievement information is tabular content. In the given task of training the model to identify the number of individuals scoring above 80 in mathematics, the display of the model can transform this task into a query statement for the database. The entire table is transformed into a database, and the answer to the question is transformed into a data query statement. However, this model is limited to specific tables, such as questions about grades in other subjects, and it is difficult to generalize to other arbitrary questions. It is difficult for us to classify drivers' mental workload directly. Table-based automated question and answer extract answers directly from the table. For example, the table is the weather conditions for a week. When the question is whether Tuesday is sunny, the model can choose the correct answer from the features of Tuesday. This model learns the model's global semantic understanding, and the answer is already on the table. The final type is table-based fact-checking, which is an output that determines whether the current table satisfies certain facts based on the table's input information [27]. These outputs are typically multi-categorized and correspond to various situations. Based on the tabular data, we expect to output the different states of the current driver's mental workload load in the driver's mental workload classification. In conclusion, we can conclude that the classification and prediction of a driver's mental workload belong to table-based fact-checking in a tabular task. We expect to classify the driver's mental workload directly from the psychological data collected.

C. PROCESSING AND ANALYSIS OF LONG TIME SEQUENCES DATA

With the ongoing development of deep learning, there have been several significant changes in the learning algorithms for the long time sequences data in recent years. First, researchers proposed Recurrent Neural Network (RNN) based on deep learning and neural network knowledge [28], [29]. RNN will remember the temporal information in the data by using the previous time sequences' output as the input for the current sequences. However, RNN's memory is relatively short and it will forget the input over long periods. A more complex model Long Short-Term Memory (LSTM) is proposed to better remember long sequences data. It will discard previously unwanted information selectively while deciding whether to update new information in the memory unit. A structure like this allows the previous information to be kept for a long time without being discarded. On the other hand, to enhance the correlation between input data. In the representation of temporal data, word embedding is also used [30], [31]. In high-dimensional space, it can represent semantically similar words. After combining the word embedding representations, an attention mechanism is also introduced to the learning of long time sequences to display the specific important representations. During this time, the Transformer model is a significant departure from the previous model, completely replacing the RNN model structure and running parallel to the sequence problem [32], [33]. Furthermore, Transformer not only improves the ability to process long time sequences data but also incorporates attention mechanisms. It is still the standard technique for processing long sequences data. Subsequently, BERT based on Transformer takes a step further to demonstrate that Transformer has excellent generalization capabilities for numerous tasks [34]. Tapas is the first Transformer model inspired by BERT for tabular data. Gradually, Table-based Transformer models are increasingly being proposed. However, for the driver's mental workload classification task, the positional encoding introduced by these models through the use of the Transformer can affect the correlation between unordered features such as HR and EDA. As a result, the question of how to reasonably model on the acquired physiological tabular data remains an open question.

III. METHODS

A. OVERALL APPROACH

For tables with different column orders, LTS-MPF can produce uniform output. First, the table information will be converted into a form that LTS-MPF can input, including token, segment, cell position, row position, rank, and so on. The organized table data will be input to LTS-MPF, which is a model built from a self-attentive layer. Subsequently, we use the output of the model to implement the classification and prediction of that temporal psychological data.

LST-MPF is constructed from the Transformer model. For the original table data, we need to convert the table content into a pattern that the Transformer model can receive, that is to restore the original data into feature embeddings. The overall framework of LST-MPF is shown in Figure 1. For tables with different column order, they are split into a uniform input form before being input to LST-MPF. Then after learning of LST-MPF, the model will output the corresponding embedding features in the last layer. We use the feature vector with the h[cls] flag bit for the final classification, or prediction.

B. PRE-PROCESSING OF TABLE DATA

Tables can be organized in a variety of ways, and different column orderings can result in various table forms. These tables, however, essentially represent the same meaning. For example, the three tables in Figure 1 each have different columns, but they all express the same meaning. However, data location information must be entered as an additional feature in the Transformer model. Variations in the columns can also cause input differences, which can affect the model's output. Forcing various inputs to produce the same output would decrease the model's ability to generalize. As a result, we remove the column position information while recording table information. We keep track of each cell's token and segment in the original table, as well as its cell location and row position, and whether it is distinguished by rank as belonging to the table header or content.

1) EMBEDDING FEATURES OF TABLE DATA

Specifically, LTS-MPF uses flattened text as input, that is the table content is flattened, and then the entire table content is input at once. For classification or prediction tasks, we borrow the strategy from Bert's method and use [CLS] as a prefix. To handle the table task, we introduce embeddings such as token, segment, cell position, row position, and rank to understand the overall table better. Suppose, for any tabular data after flattening, $S = \{v_1, v_2, \cdots, v_n\}$, where n denotes the length of the whole table. The input to LTS-MPF is a combination of the following feature embeddings, as in

$$\begin{aligned} token(X) &= \{x_{v_1}, x_{v_2}, \cdots, x_{v_n}\} \\ segment(G) &= \{g_{seg_1}, g_{seg_2}, \cdots, g_{seg_n}\} \\ cell(C) &= \{c_{cell_1}, c_{cell_2}, \cdots, c_{cell_n}\} \\ row(R) &= \{r_{row_1}, r_{row_2}, \cdots, r_{row_n}\} \\ rank(Z) &= \{z_{rank_1}, z_{rank_2}, \cdots, z_{rank_n}\} \end{aligned}$$

where seg_i, $cell_i$, row_i, $rank_i$ correspond to the segment, cell, row and rank id of the i_th token, respectively.

2) POSITION ENCODING

For the order of the different fields of the record, such as $Cell_i$, or row_i information, we need to perform position encoding based on the starting position display of the table. The dimensionality between position encoding and embedding features is the same so that they can be directly summed up. In LTS-MPF, we use sine and cosine functions of different frequencies for encoding,

$$\begin{aligned} PE_{(pos,2i)} &= \sin(pos/10000^{2i/d_{model}}) \\ PE_{(pos,2i+1)} &= \cos(pos/10000^{2i/d_{model}}) \end{aligned}$$

where pos is the position, and i is the dimension. Each dimension of the position encoding corresponds to a sine curve. These wavelengths form a geometric progression from 2π to $10000 \cdot 2\pi$. We chose this function because we assume that it allows the model to easily learn to pay attention to the relative positions, since for any determined offset k, $PEpos + k$ can be expressed as a linear function of $PEpos$.

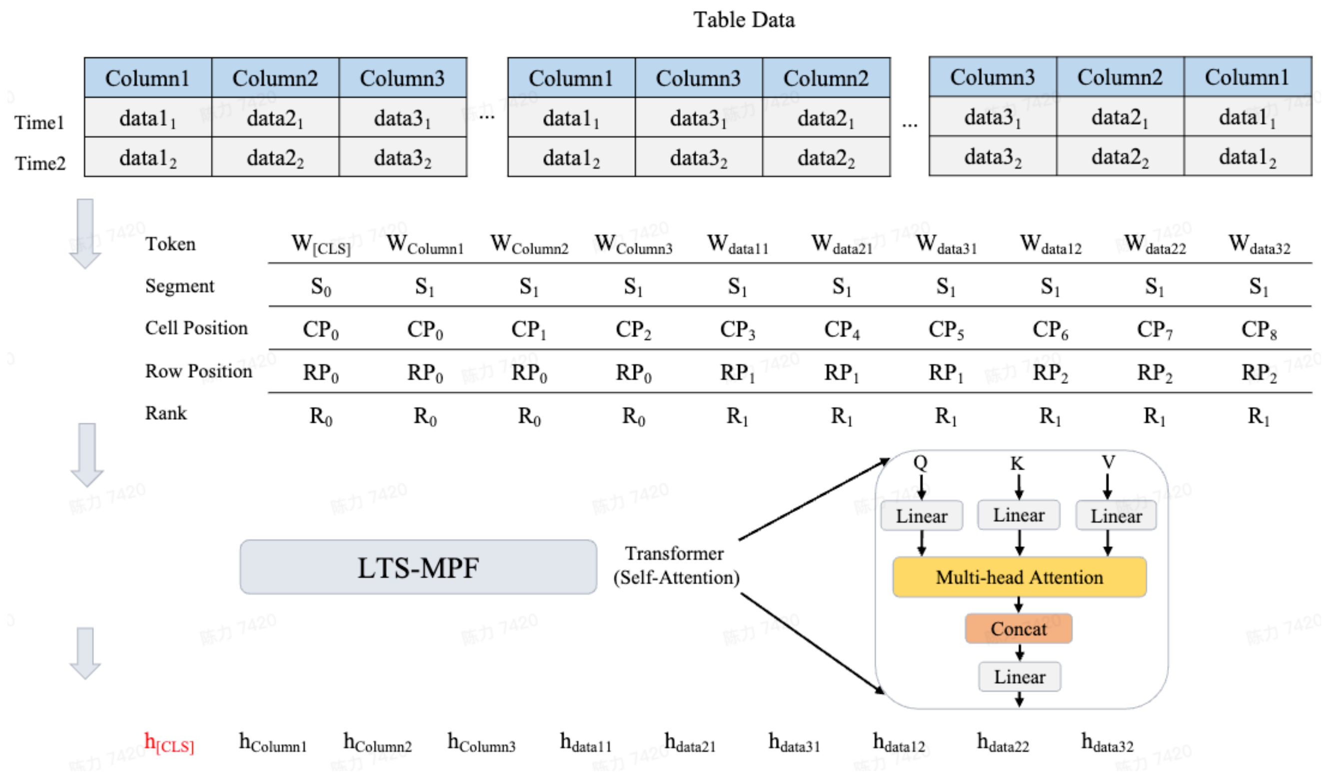

FIGURE 1. **LTS-MPF general framework diagram.**

C. LTS-MPF

For LTS-MPF, the model is also a transformer-based model. Each Transformer layer includes a multi-headed self-attentive sublayer, where each token can pay attention to all tokens. The transformer structure is actually an extension of the self-attentive mechanism. It is similar to the variation of convolutional layers in convolutional neural networks, where the model can learn more important data better by gradient descent algorithm. In the model as Figure 1, Q is used for query, K is used for keyword retrieval, and V represents the corresponding result. Where Q, K, and V all come from changes in the data itself, that is the self-attentive mechanism. Subsequently, the output is passed through the fully connected layer and the classifier, then the final classification result can be obtained.

1) SELF ATTENTION

The Attention function can be described as mapping query and a set of key-value pairs to an output, where query, key, value, and output are all vectors. The output is a weighted sum of values, where the weights assigned to each value are computed by the compatibility function of query with the corresponding key. For the input feature $X = x_v$, after three learnable matrix variations W^Q, W^K and W^V, the result can be projected to W^Q, W^K and W^V.

$$Q = XW^Q, \quad V = XW^V, \quad K = XW^K$$

In practice, we simultaneously compute a set of query's attention functions and combine them into a matrix Q. The key and value are also packed together into matrices K and V. We compute the output matrix as,

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

where, d_k denotes the number of dimensions of the input feature x_v.

2) MULTI-HEAD ATTENTION

We find that it is better to use different linear mappings of query, key and value to dk, dk and dv dimensions, respectively. Each attention function can divide the original input feature dimension into n parts, and each part performs a separate self-attention operation, and the subsequent results are then aggregated to effectively improve the performance of the model. This mechanism is also known as multi-head attention mechanism.

Multi-head attention allows different representation subspaces of the model to jointly focus on information at different locations. If there is only one attention head, its average value will weaken this information.

$$Multihead(Q, K, V) = Concat(head_1, \ldots, head_h)W^O$$
$$wherehead_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$$

where the mapping is the parameter matrix $W_i^Q \in \mathbb{R}^{d_{model} \times d_Q}$, $W_i^K \in \mathbb{R}^{d_{model} \times d_K}$, $W_i^V \in \mathbb{R}^{d_{model} \times d_V}$ and $W^O \in \mathbb{R}^{hd_V \times d_{model}}$. In this work, we use h=4 parallel attention layers or heads. For each head, we use $d_K = d_V = d_{model}/h = 64$. Although split into multiple heads, the total number of dimensions of the input features does not change, so the total computational cost is similar to that of single head attention with all dimensions.

3) FFN FEED-FORWARD MODEL FFN

In addition to the attention sublayer, each layer of the model contains a feedforward network of fully connected layers. This feedforward network is applied individually and identically to each location. It consists of two linear transformations with a ReLU activation between them.

$$FFN(x) = max(0, xW_1 + b_1)W_2 + b_2$$

This layer efficiently organizes high attention features and outputs the most useful features to the next structure.

4) SOFTMAX EMBEDDING AND SOFTMAX

At the end of our model, the output feature embedding has the same weight as the fully connected layer between the classifiers. Similar to other sequence models, we use the learned embedding features converted to vectors of the dimension d_{model}. We also use linear transformations and softmax functions to convert the decoder output into probabilities for classifying and predicting psychological situations.

During the smooth process, the model is trained with supervised data, which allows the model to converge. And for testing, we only need to use this signifier h [cls] to achieve the final classification and prediction.

IV. EXPERIMENTAL SETUP

A. DATA AND EQUIPMENT

21 participants—15 men and 6 women—aged between 21 and 32 years and reporting 1 to 11 years of driving experience participated in this study as Table 1. Participants from South China University of Technology who were in good physical and mental health made up the participants. Each one had a valid driver's permit and gave their permission for video and physiological signals to be captured while they were driving. Participants' vision had an acuity of at least 1.0, according to a new national standard visual acuity chart (scale: 0.01-2.0). In order to confirm their willingness to take part in the experiment, participants signed a statement.

Before starting out, drivers would receive a map of the route. Drivers drove a lavida on the expressway. We ran a 66.7-kilometer test on the Erenhot-Guangzhou Expressway from Tangjia Toll Station to Guangning Toll Station in Guangdong Province. Because there were different driving scenarios, such as a straight road, a curve, a ramp, a tunnel, and changing between three or four lanes, the data features of the physiological indicators obtained were also different. Physiological signals were recorded using the sensor BIOPAC MP160 to ensure the validity of the experimental findings. On the left and right sides of the chest as well as the waist, an ECG sensor was fastened. An EDA sensor was attached to the index and middle fingers of the non-dominant hand. The ECG input signal was set to between ±10 mv, the sampling rate was 2000 beats per second, and the maximum response of the EDA was set at 50/mu S. The observer seated on the passenger side to connect the BIOPAC MP160 to the AcqKnowledge 5.0 software on the laptop, as well as to receive and store experimental data. Environment for processing experimental data: The software environment was made up of Python 3.7 and AcqKnowledge 5.0. AcqKnowledge 5.0 was primarily used to retrieve physiological signals (such as ECG and EDA), and Figure 2 depicts the experimental setup. Extensive data analysis was mostly carried out using Python 3.7 after data extraction.

In one day, two drivers participated in the driving experiment each driving for half a day. The drivers' physiological responses would be monitored by sensors on their bodies and fingertips. After getting the driver's approval, the observer turned on BIOPAC MP160 and AcqKnowledge 5.0 and the experiment started. The observer's role was to assist with device connections, respond to the driver's inquiries, and monitor the accuracy of the physiological signal collection while the driver was driving. Driving time from 8:00 to 19:00, including dinner and rest intervals from 12:00 to 14:00, totaled 8 hours and 20 minutes. The two ten-minute breaks occurred at the beginning and end of the driving. The driver sat in the passenger seat, his eyes closed, and the automobile was silent during this time. The data collected at this point provided as a baseline for later data processing. The whole experimental period was 42 days to ensure that each person would conduct at least two days of driving experiments and two non-consecutive days. Therefore, each driver not only experienced a variety of natural scenarios, such as daytime, dusk, sunny, rainy days, etc. but also experienced the straight road, curved road, on-ramp and lane changes, etc., for 8 hours per day, so the data collected on psychological indicators were also diverse. Discontinuous driving events for 8 hours per day also provided data on psychological characteristics when driving with fatigue. Because the same person drove for two non-consecutive days, it eliminated the tiny changes in psychological characteristics caused by experienced driving, which might result in unrepresentative data.

The final experiment collected 21,648 sets of data, of which 1,472 sets were invalid and there were 20,176 sets of usable data. The train and test sets are set up according to 80% and 20%, distributed as 16140 and 4036 sets. For the experimental results, we conducted 5 experiments on each setting, and the results are taken as mean.

B. DATASETS AND EVALUATION

Features are taken from the time interval for the original data acquired from a sensor based on the experiments mentioned above. The data is promptly processed utilizing resampling, noise reduction, and filtering methods. In terms of noise reduction, this study first reduces the sampling rate of the acquired data from 2000.000samples/secod to 31.250samples/secod, and then applies a low pass filter with the Frequency outoff set to 3Hz. After completing the above steps, a data extraction is carried out where the intervel

TABLE 1. Experimental participant basic information.

Driver characteristics	Amount	Ratio/%	Mean	Std
Male	15	71.4		
Female	6	28.6		
Age 21-24 years	2 years	9.5	27.3 years	3.7
Age 25-28 years	14 years	66.7		
Age 29-32 years	5 years	23.8		
Driving experience of 5 years or less	13 years	61.9	5.3 years	2.6
Driving experience6-11 years	8 years	38.1		

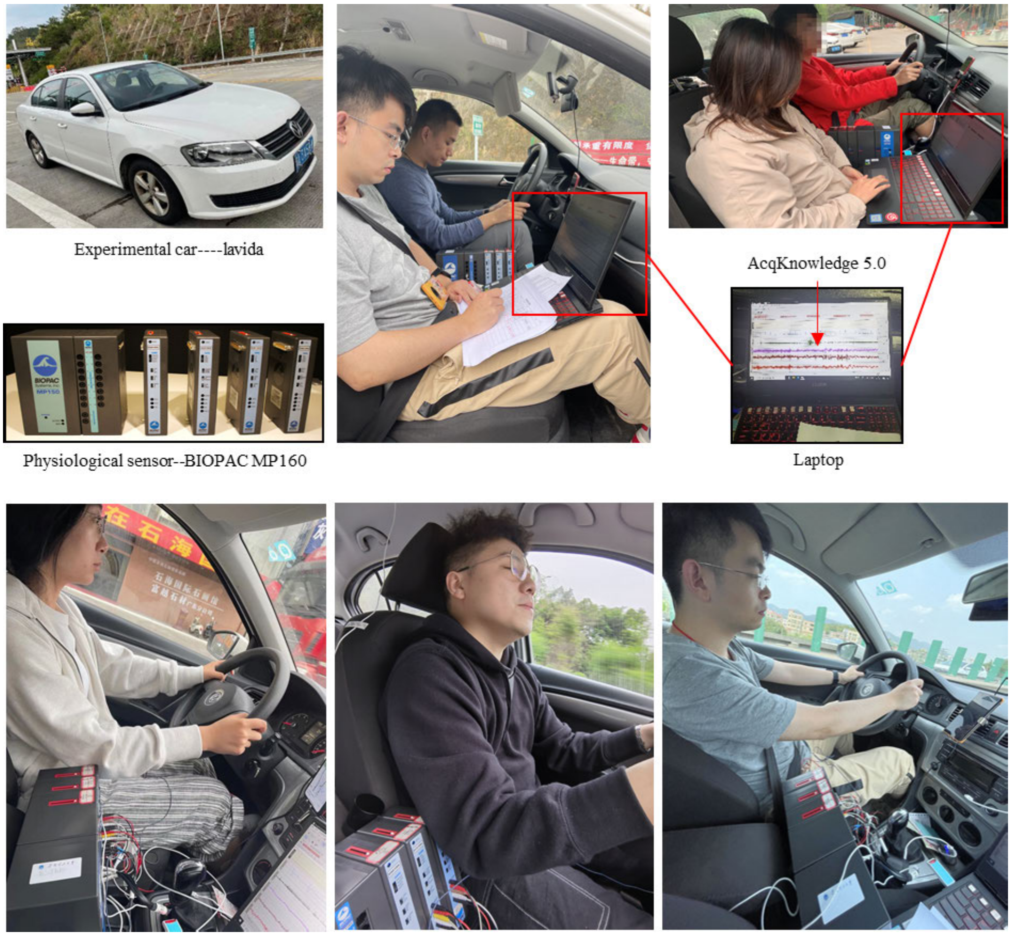

FIGURE 2. Experimental equipment.

window is 1 second, thus reducing the effect of noise during driving.

After the experiment, we use a traditional method, NASA-TLX [6] belonging to the subjective measurement, to label the original data. NASA-TLX is a popular and widely used way to evaluate subjective feeling of drivers from six dimensional indicators [35], with scores spanning 1-10.

- **Mental Demands**:Driving requires mental demands such as thinking, decision making, memory, and other intuitive processes.
- **Physical Demands**: Is it easy or difficult to move your hands and feet while driving? Is your body as a whole calm or tired?
- **Temporal Demands**: Do you sense any time constraints when driving? Is the work completion rate rapid or slow?
- **Own Performance**: Do you believe you have completed the driving test successfully? Are you happy with how you performed?
- **Effort**: How much effort was put in the completion procedure to ensure a successful completion of the needed operation?
- **Frustration**: How insecure/frustrated/angry/stressed/ upset did you feel during the driving task?

For a total of 15 comparisons, all six-dimensional indicators are aggregated and assessed for relevance one by one. The number of times an index is selected determines its weight, which is indicated by w_i. Each index's score on this scale is denoted by r_i. Finally, a weighted average of each index is determined to yield the mental workload score, which is derived using the formula below.

$$\text{weighted average score of mental workload} = \frac{1}{15}\sum_{i=1}^{6} w_i r_i$$

Electrocardiograms (ECG) have been used in numerous studies as the most obvious and essential sign of changes in drivers' mental workload. In this paper, two distinct factors, heart rate growth rate (HR_growth rate) and heart rate variable (HRV), are being studied. Heart rate (HR) is the average number of times the heart beats in a given amount of time. The heart rate may show how hard the heart is working depending on the activity. It is one of the most important physiological indicators of the human body. The HR_growth rate measures how much a driver's heart rate varies at any given time, and the index can take individual variations into account. A driver may feel considerable discomfort if their heart rate increases by more than 20%, according to certain studies [36]. The following is how the HR_growth rate is calculated:

$$H_i = \frac{h_i - \overline{h}}{\overline{h}} \times 100\%$$

where h_i is the HR value at a certain point in a period, and H_i is the HR growth rate at that point. The average HR throughout that time is $\overline{h}$.

Heart rate variability (HRV) features depend on inter-beat-interval (IBI) measurements that the time between two consecutive beats. An investigation of the metrics and geometric distribution properties of the time series in RR intervals is called a time-domain analysis of HRV. The root mean square of the difference of all successive RR intervals (RMSSD) and the standard deviation of RR intervals (SDNN) are two often utilized indicators. A collection of successive RR intervals is referred to as an RR time series. RR stands for the time interval between two succeeding beats (R peaks) in the ECG.

$$SDNN = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(RR_i - \overline{RR})^2}$$

where, RR_i is the i-th RR interval, and $\overline{RR}$ denotes the N-th interval's mean RR value.

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RR_{i+1} - RR_i)^2}$$

where RR_i and RR_{i+1} are two adjacent inter-RR intervals.

In earlier research, most short-term HRV parameters were investigated with a temporal window length of 5 minutes or 1 minute [37] to assure the correctness of results. However, Lu et al. [38] say that utilizing 10s as the temporal window duration has good reliability, and its findings are commonly employed in driver state recognition. On this premise, 5s is chosen as the time interval for analysis in this work.

Electrodermal activity (EDA), a characteristic electrical characteristic of human skin, is connected to the autonomic activation of the sweat glands. This emotional input is one of the most subtle. Emotional triggers are what induce sweating on the hands and feet. Every time we experience a change in mood, the EDA data substantially changes, and the AcqKnowledge 5.0 system can measure and analyze these differences. EDA can examine actual physiological signals in unconscious behavior. As the features of this experiment, the mean and standard deviation (Std) of EDA, Mean EDA and Std EDA, are employed.

Table 2 gives a list of all extracted factors.

V. EXPERIMENTS AND RESULTS

A. EFFECT OF COLUMN ORDER ON CLASSIFICATION RESULTS

The Transformer method will be affected by the table's different column order. Our proposed LTS-MPF method is sufficient to convert the table data into the model in a form that is independent of column order. The following experiments were carried out to test the effectiveness of the LTS-MPF method on the multi-factor time series forecasting task. First, we divided the same multifactor time series data into five tables (see Table 3). These tables differ only in column order but contain the same data. We then compare LTS-MPF to TAPAS, another Transformer method on tables. TAPAS also converts tables into a text-like format for model input, but ignores the effect of changes in column order. The model output changes as the order of the input table column changes. We used multi-factor data collected within a 60-second time window to train both models using configuration 2. Table 4 displays the experimental results.

Under different table configurations, our proposed LTS-MF maintains a stable and efficient classification performance. It achieves a mean correct rate of 94.34% with a variance of 0.054 under 5 sets of configurations. TAPAS, on the other hand, performs the best only in table configuration 2, with the correct rate significantly lower in all other configurations. Under all five configurations, it has a mean correct rate of 88.66% and a variance of 2.175.

These experimental results demonstrate LTS-MF's efficacy and robustness. It is unaffected by column order in the table, whereas TAPAS is extremely sensitive to column order. Furthermore, LTS-MF can exhibit a correct rate exceeding TAPAS by 3.1% even under TAPAS's best table configuration2. This demonstrates LTS-MF's superior generalization ability for predicting driver's mental workload.

B. EFFECT OF TIME SERIES LENGTH ON CLASSIFICATION RESULTS

LTS-MPF is a table-based temporal classification model that can utilize both structured and temporal information in tables. It takes the whole table as input, with each row representing one moment of data. To examine the effect of timing length on LTS-MPF, we divide the dataset into time intervals ranging from 40 seconds to 80 seconds. We can then simulate the data sampling frequency and observation window in various scenarios.

TABLE 2. Summary of all extracted factors.

Type of Factors	Name and Definition	Unit
ECG	HR Growth Rate: the growth rate of heart rate variation in one second	%
	SDNN: Standard deviations of all RR intervals	s
	RMSSD: Root mean square of successive differences between adjacent RR intervals	s
EDA	Mean EDA: Average value of electrodermal activity within five seconds	μS
	Std EDA: Standard deviation of electrodermal activity within five seconds	μS

TABLE 3. Five table configuration of features.

Table configuration 1	Mean EDA	Std EDA	SDNN	RMSS	HR_growth rate
Table configuration 2	HR_growth rate	SDNN	RMSS	Mean EDA	Std EDA
Table configuration 3	SDNN	RMSS	HR_growth rate	Std EDA	Mean EDA
Table configuration 4	Std EDA	Mean EDA	SDNN	RMSS	HR_growth rate
Table configuration 5	RMSS	HR_growth rate	Mean EDA	SDNN	RMSS

TABLE 4. Correct rate of different table configurations within 60-Second.

	Table configuration 1	Table configuration 2	Table configuration 3	Table configuration 4	Table configuration 5
TAPAS	90.1	91.2	87.4	85.7	88.9
LTS-MF	94.4	94.3	94.3	94.4	94.3

TABLE 5. Correct rate of different method within different time windows.

	Data_40s	Data_50s	Data_60s	Data_70s	Data_80s
NN	76.2	74.4	71.5	68.4	66.8
SVM	87.5	86.4	83.2	80.6	77.8
RF	90.4	89.5	88.5	86.1	83.2
RNN	89.2	87.2	85.5	84.2	81.2
LSTM	90.3	90.5	88.9	88.1	86.4
TAPAS	90.8	91.1	91.2	89.4	88.5
LTS-MPF	94.1	93.6	94.3	92.5	91.4

We ran experiments with a variety of methods, including traditional machine learning methods like neural networks, support vector machines, and random forests, as well as temporal or table-related methods like RNN, LSTM, and TAPAS. Due to traditional machine learning methods that cannot handle temporal information, their results are an average of classification results at each moment. While RNN and LSTM can deal with temporal data, they ignore structured data in tables. TAPAS also makes use of the Transformer structure. In configuration 2, the data column order is used, and the experimental results are shown in Table 5.

LTS-MPF achieves optimal or near-optimal performance at various timing lengths, as shown in Table 5, and has significant advantages over other methods. For example, at a timing length of 40 seconds, LTS-MPF achieves a correct rate of 94.1%, while the closest method to it is TAPAS with only 90.8%. At a timing length of 80 seconds, LTS-MPF achieves a correct rate of 91.4%, while the closest methods to it are TAPAS and LSTM with only 88.5% and 86.4%, respectively.

These results demonstrate the utility of LTS-MPF for both temporal and structured data. Because traditional machine learning methods cannot handle temporal data, they perform poorly in all configurations. RNN and LSTM can deal with temporal data, but they ignore structured data in tables. Through a self-attentive mechanism, LTS-MPF, on the other hand, can effectively use both temporal and structured information to capture potential patterns and patterns in tables.TAPAS is a model designed specifically for the table quizzing task that encodes tables and questions using the Transformer structure. However, in our task, the question text is not explicitly provided, but the classification results must be inferred from the whole table, so TAPAS is not suitable for our task scenario. In contrast, LTS-MPF is able to leverage the entire table as input and capture the relationship between temporal and structured information through a self-attentive mechanism. For example, in a dataset where each row represents relevant data about a character's mental workload at a specific point in time, we need to calculate the overall mental workload of a driver based on the entire table. In this case, relying on individual time points or individual characteristics alone is insufficient to make an accurate judgment, but rather requires consideration of how the driver as a whole change between time points. This necessitates that the model be able to process both temporal and structured data, as well as learn the underlying patterns and patterns. All these validate the effectiveness of LTS-MPF.

We counted the confusion matrix results for 40s, 60s, and 80s timings, and the results are shown in Figure 3.In Figure 3 LML, MML, and HML, respectively, are abbreviations for low mental workload, medium mental workload, and high mental workload.

The experimental results show that the LTS-MPF method's classification effectiveness decreases as the time series lengthens, but the decrease is not statistically significant. One possible explanation is that as the time series lengthens, the feature changes become more complex, making it difficult for the classification model to capture useful information. Second, we calculate the recall of LML at 40s to be 0.9618. Similarly, MML and HML have recalls of 0.9018 and 0.9262, respectively. At 60s, the recall of LML, MML, and HML is

	LML	MML	HML	Recall
LML	2820	73	39	0.9618
MML	49	1102	71	0.9018
HML	35	25	753	0.9262
Precision	0.9711	0.9183	0.8725	0.9412

LTS-MPF Confusion Matrix Results for 40s

	LML	MML	HML	Recall
LML	2811	69	35	0.9643
MML	52	1110	65	0.9046
HML	41	21	763	0.9248
Precision	0.9680	0.9250	0.8841	0.9430

LTS-MPF Confusion Matrix Results for 60s

	LML	MML	HML	Recall
LML	2723	79	49	0.9551
MML	87	1074	71	0.8718
HML	94	47	743	0.8405
Precision	0.9377	0.895	0.8610	0.9140

LTS-MPF Confusion Matrix Results for 80s

FIGURE 3. LTS-MPF model's confusion matrix results.

0.9643, 0.9046, and 0.9248, respectively. At 80s, the recall of LML, MML, and HML is 0.9551, 0.8718, and 0.8405, respectively. This means that among the three time series, LML has the highest recall and HML has the lowest recall. This could imply that the LTS-MPF method is better at identifying positive cases for LML while misclassifying positive cases as negative (false negatives) for HML. Finally, for each category of precision, the precision of LML at 40s is 0.9711. MML and HML precision are 0.9183 and 0.8725, respectively. At 60s, the precision of LML, MML, and HML is 0.9680, 0.9250, and 0.8841, respectively. At 80s, the precision of LML, MML, and HML is 0.9377, 0.8950, and 0.8610, respectively. This means that for all three time series, LML has the highest precision and HML has the lowest precision. This could imply that the LTS-MPF method is better at excluding negative cases (true negatives) for LML while misclassifying negative cases as positive cases (false positives) for HML. In summary, the LTS-MPF method can adapt to data with varying time series lengths while maintaining high overall accuracy and stability. However, there are some distinctions between the various categories. In terms of recall and accuracy, LML outperforms the other two categories, whereas HML falls short of the other two categories.

C. EFFECT OF TIME-SERIES DATA ON PREDICTION RESULTS

LTS-MPF is a time-series processing method that can not only classify the driver's mental workload in the current time series but also predict it in the next time series. We also compared it with other methods, and the experimental results are presented in Table 6.

The experimental results demonstrate that LTS-MP can classify and predict driver's mental workload for both current and future time series. According to Table 6, LTS-MPF achieves the highest classification accuracy of 93.5%, 92.3%, and 91.1% on all three types of temporal data, which is much higher than the classification accuracy of other machine learning algorithms such as NN, SVM, RF, RNN, and LSTM. LTS-MPF also provides a considerable benefit over TAPAS,

TABLE 6. Prediction results of different method within different time windows.

	Data_5s	Data_10s	Data_15s
NN	71.1	65.8	63.2
SVM	80.8	77.9	74.4
RF	82.1	78.6	76.4
RNN	84.8	83.7	80.5
LSTM	88.3	87.4	86.1
TAPAS	90.5	88.9	87.9
LTS-MPF	93.5	92.3	91.1

TABLE 7. Accuracy of LTS-MPF under different time windows with different number of blocks and heads.

		Data_40s	Data_60s	Data_80s
2 block	1 head	92.1	93.4	89.2
	4 head	94.2	94.1	90.2
	6 head	94.1	93.8	90.7
4 block	1 head	93.4	94.0	90.5
	4 head	94.1	94.3	91.4
	6 head	94.3	94.5	91.7
6 block	1 head	93.9	94.1	91.2
	4 head	94.0	94.3	92.3
	6 head	94.2	94.4	92.4

which has the same Transformer results. All of the experimental data show that LTS-MPF has excellent temporal processing and generalization capabilities.

D. MODEL ANALYSIS

The encoder and decoder of LTS-MPF can be made up of numerous blocks, and each Transformer module can have multiple attention heads. This structure can increase the model's representation and generalization abilities. We also confirmed multiple LTS-MPF structures in our experiments, and the results are provided in Table 7.

According to the experimental results, increasing the number of both blocks and heads can increase the model's accuracy on various tasks. For the same amount of blocks, employing 4 or 6 heads produces better outcomes than using one head. Increasing the number of blocks with the same number of heads can also increase model performance. Finally, LTS-MPF is a versatile and effective model architecture that, in terms of parameters and layer count, may be adapted to various application circumstances.

VI. CONCLUSION

The driver's mental workload is a significant component influencing driving safety, however, there are few appropriate and precise assessment methods. In this paper, we propose a classification and prediction method based on time-series multi-feature biopsychological data in this research, and we utilize the LTS-MPF (long time sequences and multiple physiological factors) model to assess and predict the driver's mental workload. Sensors are used to collect biopsychological data from drivers and to convert it into tabular data. Then, for each row of tabular data, we embed it in a vector and feed the entire table into the LTS-MPF model. The LTS-MPF model allows for time series correlation analysis and reduces uncorrelatedness between feature series. In our experiments, we evaluate the effectiveness of the LTS-MPF model with other methods for classifying and predicting the driver's mental workload and discover that the LTS-MPF model has considerable advantages. The experimental findings demonstrate that the LTS-MPF approach has a high overall accuracy at various time series lengths and a good balance between different categories. When compared to earlier methods, the LTS-MPF method handles time-series multi-feature data better and has superior generalization and prediction capabilities. We believe that the LTS-MPF model can be utilized not only to assess current mental workload but also to anticipate future mental load changes, giving data support for early warning of unsafe driving behaviors.

Although the LTS-MPF model has demonstrated outstanding results in identifying and forecasting driver mental load, it does have significant limits and weaknesses. (1) The LTS-MPF model requires a considerable amount of labeled data for training, and acquiring and labeling this data is time-consuming and labor-intensive. (2) The LTS-MPF model can only manage single table data and cannot handle correlation and consistency across many tables. (3) The LTS-MPF model has not yet included the impact of external elements on the driver's mental load, such as driving environment, road conditions, and traffic conditions. All of these are challenges that we need to look into deeper in the future.

REFERENCES

[1] T. G. Hicks and W. W. Wierwille, "Comparison of five mental workload assessment procedures in a moving-base driving simulator," *Human Factors, J. Human Factors Ergonom. Soc.*, vol. 21, no. 2, pp. 129–143, Apr. 1979.

[2] F. T. Eggemeier, G. F. Wilson, A. F. Kramer, and D. L. Damos, "Workload assessment in multi-task environments," in *Multiple-Task Performance*. Boca Raton, FL, USA: CRC Press, 2020, pp. 207–216.

[3] G. Jahn, A. Oehme, J. F. Krems, and C. Gelau, "Peripheral detection as a workload measure in driving: Effects of traffic complexity and route guidance system use in a driving study," *Transp. Res. F, Traffic Psychol. Behaviour*, vol. 8, no. 3, pp. 255–275, May 2005.

[4] V. Cantin, M. Lavallière, M. Simoneau, and N. Teasdale, "Mental workload when driving in a simulator: Effects of age and driving complexity," *Accid Anal Prev*, vol. 41, no. 4, pp. 763–771, 2009.

[5] M. S. Young, K. A. Brookhuis, C. D. Wickens, and P. A. Hancock, "State of science: Mental workload in ergonomics," *Ergonomics*, vol. 58, no. 1, pp. 1–17, Jan. 2015.

[6] G. Sandra Hart and E. LowellStaveland, "Development of NASA-TLX (task load index): Results of empirical and theoretical research," *Adv. Psychol.*, vol. 52, pp. 139–183, Apr. 1998.

[7] Z. H. Khan, T. A. Gulliver, and K. S. Khattak, "A novel macroscopic traffic model based on distance headway," *Civil Eng. J.*, vol. 7, pp. 32–40, Dec. 2021.

[8] Z. H. Khan, T. A. Gulliver, and W. Imran, "A macroscopic traffic model based on the safe velocity at transitions," *Civil Eng. J.*, vol. 7, no. 6, pp. 1060–1069, Jun. 2021.

[9] K. A. Brookhuis, C. J. G. van Driel, T. Hof, B. van Arem, and M. Hoedemaeker, "Driving with a congestion assistant; mental workload and acceptance," *Appl. Ergonom.*, vol. 40, no. 6, pp. 1019–1025, Nov. 2009.

[10] M. Cardoso and L. A. Gontijo, "Evaluation of mental workload and performance measurement: Nasa TLX and swat," *Gesto Produo*, vol. 19, no. 4, pp. 873–884, 2012.

[11] F. P. D. Silva, "Mental workload, task demand and driving performance: What relation?" *Proc. Social Behav. Sci.*, vol. 162, pp. 310–319, Dec. 2014.

[12] T. Butmee, T. C. Lansdown, and G. H. Walker, "Mental workload and performance measurements in driving task: A review literature: Volume VI: Transport ergonomics and human factors (TEHF), aerospace human factors and ergonomics," in *Proc. 20th Congr. Int. Ergonom. Assoc. (IEA)*, 2019, pp. 1–9.

[13] D. Kukolja, S. Popović, M. Horvat, B. Kovać, and K. Ćosić, "Comparative analysis of emotion estimation methods based on physiological measurements for real-time applications," *Int. J. Hum.-Comput. Stud.*, vol. 72, nos. 10–11, pp. 717–727, Oct. 2014.

[14] Z. Palatinus, M. Volosin, E. Csábi, E. Hallgató, E. Hajnal, M. Lukovics, S. Prónay, T. Ujházi, L. Osztobányi, B. Szabó, T. Králik, and Z. Majó-Petri, "Physiological measurements in social acceptance of self driving technologies," *Sci. Rep.*, vol. 12, no. 1, p. 13312, Aug. 2022.

[15] H. Aghajani, M. Garbey, and A. Omurtag, "Measuring mental workload with EEG+fNIRS," *Frontiers Human Neurosci.*, vol. 11, Jul. 2017, Art. no. 00359.

[16] N. E. J. Asha, Ehtesum-Ul-Islam, and R. Khan, "Low-cost heart rate sensor and mental stress detection using machine learning," in *Proc. 5th Int. Conf. Trends Electron. Informat. (ICOEI)*, Jun. 2021, pp. 1369–1374.

[17] S. B. Kotsiantis, I. D. Zaharakis, and P. E. Pintelas, "Machine learning: A review of classification and combining techniques," *Artif. Intell. Rev.*, vol. 26, no. 3, pp. 159–190, Nov. 2006.

[18] T. Luong, N. Martin, A. Raison, F. Argelaguet, J.-M. Diverrez, and A. Lécuyer, "Towards real-time recognition of users mental workload using integrated physiological sensors into a VR HMD," in *Proc. IEEE Int. Symp. Mixed Augmented Reality (ISMAR)*, Nov. 2020, pp. 425–437.

[19] A. C. Marinescu, S. Sharples, A. C. Ritchie, T. Sánchez López, M. McDowell, and H. P. Morvan, "Physiological parameter response to variation of mental workload," *Human Factors, J. Human Factors Ergonom. Soc.*, vol. 60, no. 1, pp. 31–56, Feb. 2018.

[20] K. Ryu and R. Myung, "Evaluation of mental workload with a combined measure based on physiological indices during a dual task of tracking and mental arithmetic," *Int. J. Ind. Ergonom.*, vol. 35, no. 11, pp. 991–1009, Nov. 2005.

[21] G. Durantin, J.-F. Gagnon, S. Tremblay, and F. Dehais, "Using near infrared spectroscopy and heart rate variability to detect mental overload," *Behavioural Brain Res.*, vol. 259, pp. 16–23, Feb. 2014.

[22] G. F. Wilson, "An analysis of mental workload in pilots during flight using multiple psychophysiological measures," *Int. J. Aviation Psychol.*, vol. 12, no. 1, pp. 3–18, Jan. 2002.

[23] J.-H. Zhang, X.-Y. Wang, M. Mahfouf, and D. A. Linkens, "Use of heart rate variability analysis for quantitatively assessing operator's mental workload," in *Proc. Int. Conf. Biomed. Eng. Informat.*, May 2008, pp. 1–11.

[24] T. Reinhardt, C. Schmahl, S. Wüst, and M. Bohus, "Salivary cortisol, heart rate, electrodermal activity and subjective stress responses to the mannheim multicomponent stress test (MMST)," *Psychiatry Res.*, vol. 198, no. 1, pp. 106–111, Jun. 2012.

[25] M. A. Khalid, V. Jijkoun, and M. D. Rijke, "Machine learning for question answering from tabular data," in *Proc. 18th Int. Conf. Database Expert Syst. Appl. (DEXA)*, Sep. 2007, pp. 1–12.

[26] A. Majumdar, G. Ymeri, S. Strumbelj, J. Buchmüller, U. Schlegel, and D. A. Keim, "Earthquake investigation and visual cognizance of multivariate temporal tabular data using machine learning," in *Proc. IEEE Conf. Vis. Analytics Sci. Technol. (VAST)*, Oct. 2019, pp. 136–137.

[27] M. Holecek, A. Hoskovec, P. Baudiš, and P. Klinger, "Table understanding in structured documents," in *Proc. Int. Conf. Document Anal. Recognit. Workshops (ICDARW)*, vol. 5, Sep. 2019, pp. 158–164.

[28] B. Hidasi, M. Quadrana, A. Karatzoglou, and D. Tikk, "Parallel recurrent neural network architectures for feature-rich session-based recommendations," in *Proc. 10th ACM Conf. Recommender Syst.*, Sep. 2016, pp. 1–10.

[29] T. Mikolov, M. Karafiát, L. Burget, J. Černocký, and S. Khudanpur, "Recurrent neural network based language model," in *Proc. Interspeech*, Makuhari, Chiba, Japan, Sep. 2010, pp. 1–5.

[30] Z. Meng, S. Watanabe, J. R. Hershey, and H. Erdogan, "Deep long short-term memory adaptive beamforming networks for multichannel robust speech recognition," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Mar. 2017, pp. 271–275.

[31] P. R. Vlachas, W. Byeon, Z. Y. Wan, T. P. Sapsis, and P. Koumoutsakos, "Data-driven forecasting of high-dimensional chaotic systems with long short-term memory networks," *Proc. Roy. Soc. A, Math., Phys. Eng. Sci.*, vol. 474, no. 2213, May 2018, Art. no. 20170844.

[32] S. Cundeva, "A transformer model based on the Jiles-Atherton theory of ferromagnetic hysteresis," *Serbian J. Electr. Eng.*, vol. 5, no. 1, pp. 21–30, 2008.

[33] M. Popel and O. Bojar, "Training tips for the transformer model," *Prague Bull. Math. Linguistics*, vol. 110, no. 1, pp. 43–70, Apr. 2018.

[34] J. Turton, D. Vinson, and R. Elliott Smith, "Deriving contextualised semantic features from BERT (and other transformer Model) embeddings," 2020, *arXiv:2012.15353*.

[35] A. Dey and D. D. Mann, "Sensitivity and diagnosticity of NASA-TLX and simplified SWAT to assess the mental workload associated with operating an agricultural sprayer," *Ergonomics*, vol. 53, no. 7, pp. 848–857, Jul. 2010.

[36] M. Fallahi, M. Motamedzade, R. Heidarimoghadam, A. R. Soltanian, and S. Miyake, "Effects of mental workload on physiological and subjective responses during traffic density monitoring: A field study," *Appl. Ergonom.*, vol. 52, pp. 95–103, Jan. 2016.

[37] S. Laborde, E. Mosley, and J. F. Thayer, "Heart rate variability and cardiac vagal tone in psychophysiological research–recommendations for experiment planning, data analysis, and data reporting," *Frontiers Psychol.*, vol. 8, p. 213, Feb. 2017.

[38] Y. Lu, X. Fu, C. Lu, E. Guo, F. Tang, J. Zhu, and H. Li, "Effects of route familiarity on drivers' psychological conditions: Based on driving behaviour and driving environment," *Transp. Res. F, Traffic Psychol. Behaviour*, vol. 75, pp. 37–54, Nov. 2020.

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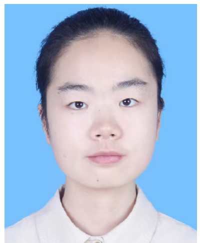

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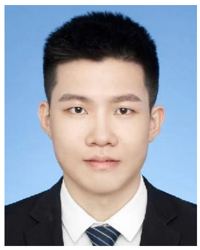

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