Assessing Dynamic Flow Experience from EEG Signals: A Processing-based Approach

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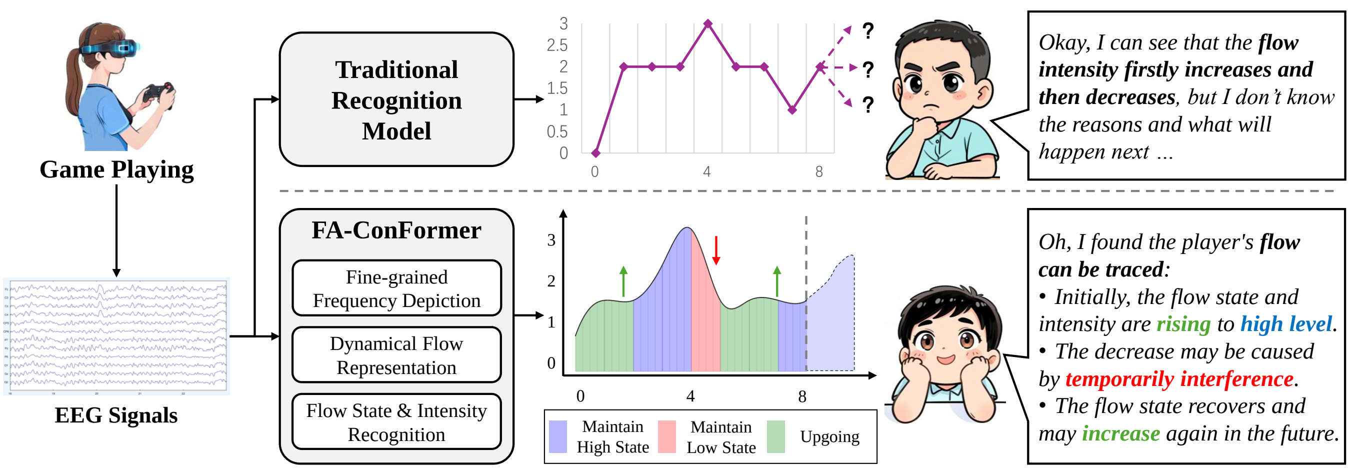

Figure 1: Illustration of dynamic flow assessment using EEG signals. Traditional methods classify flow on the intensity aspect, and it is difficult to explain the trends of flow. FA-ConFormer learns the intensity and flow states, so that it can comprehensively consider the reasons for flow changes and subsequent developments.

ABSTRACT

As an interaction experience goal, the flow experience is characterized by its subjectivity and dynamism. Exploring objective methods to assess dynamic flow states is significant in enhancing user experience design, evaluation, and optimization. This study aims to model the dynamics of the flow experience and quantify its intensity using electroencephalography signals (EEG) from the perspective of the

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process. To achieve this, an interactive task is designed to induce dynamic changes in flow, and EEG signals from participants were recorded simultaneously, to form a flow assessment dataset. Subsequently, a frequency-aware convolutional Transformer model (FA-ConFormer) was proposed to extract dynamic features from EEG, with particular optimization for capturing complex dynamic features in the frequency domain. Experimental results demonstrate that FA-ConFormer outperforms existing methods in flow state and intensity recognition, the visualization of the flow process dynamically depicting the onset, development, peak, and decline of flow with varying intensities, which help to deepen the understanding of flow experience.

CCS CONCEPTS

• **Human-centered computing → HCI design and evaluation methods**.

KEYWORDS

Flow experience, EEG signal, Transformer, Flow recognition

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1 INTRODUCTION

In human-computer interaction (HCI) activities, flow experience (short as flow) is both a critical user experience goal and an essential design objective pursued by HCI designers. Typically, flow is described as a state of complete immersion and focused engagement in the current activity [14]. When in a flow state, individuals exhibit high levels of spontaneity, fluidity, and self-involvement.Individuals subjectively enjoy the current activity and are spontaneously inclined to continue it [29, 70]. In HCI, flow experience refers to the cognitive state of concentration and immersion achieved through interactive technology [73]. Flow leads to higher task efficiency and greater satisfaction [18, 68], therefore, is widely regarded an optimal user experience and a crucial criterion to assess the quality of user experience in various HCI activities [38, 70]. Exploring effective methods to assess flow experience is a significant issue in the research on user experience in HCI.

Given the importance of flow experience, its assessment methods have become a key issue in HCI research. Traditionally, researchers have relied on subjective questionnaires and in-depth interviews to capture users' flow experiences [78]. However, these methods are retrospective and have a subjective response bias, lacking real-time characteristics [9]. Physiological signals, such as electroencephalography (EEG), electrocardiogram (ECG), and skin conductance (SCL), offer new avenues for the objective assessment of flow experience [38, 48, 55, 64]. Specifically, EEG, with its high temporal resolution and direct reflection of cognition activity, offers the potential for real-time monitoring and analysis of flow-relevant states [37, 63, 72].

However, current research on the physiological computation of flow falls short in effectively representing the dynamic nature of flow and achieving fine - grained prediction of its intensity and temporal evolution. Firstly, current research focuses primarily on the static description of flow states, such as merely determining whether a user is in a flow state [17, 38, 39, 48, 55], while neglecting the dynamic aspects of flow experiences, such as the upgoing and downgoing of flow experience. The static perspective fails to fully reveal the evolving patterns of flow experience and provides incomplete insights into user experience states. Secondly, existing EEG-based flow computation methods do not adequately address the dynamic characteristics of flow. Current research focuses mainly on extracting local characteristics from EEG signals, such as energy distribution in specific frequency bands [61]. However, these approaches fail to adequately capture the global frequency dynamics within local time frames, particularly the interactions between different frequency bands, nonlinear dynamic evolution, and subtle frequency changes [72]. Considering that the occurrence and variation process of flow is dynamic [30, 47], these advanced features are crucial for accurately reflecting the dynamics of flow and enhancing the performance of flow assessment. Nonetheless, existing methods have not addressed challenges related to these features [62], which may adversely affect the accuracy of flow state identification. Lastly, due to the absence of dynamic and process-oriented perspectives in flow description and assessment methods, existing research is struggling to effectively visualize the dynamic process of flow experience during HCI activities [28].

To address the aforementioned problem, this study aims to explore objective assessment and detection methods for the dynamic states and intensities of flow experience based on EEG signals from a process view, and to visualize users' flow experience during interactive processes. In this context, the process view emphasizes capturing the temporal evolution of flow experience as a continuous dynamic process rather than discrete static segments. This paper defines two complementary dimensions: **Progression**, which characterizes the onset, development, peak, and decline of flow intensity over time; **Transition**, which describes directional changes between flow states (e.g., upgoing, downgoing, maintaining high/low states), with the underlying potential factors driving these changes. Specifically, we first develop an HCI task to effectively induce different dynamic states and intensities of flow experience. Based on the task, we construct a multi-channel EEG dataset with labels reflecting different intensities and dynamic states of flow experience. Then, a frequency-aware convolutional Transformer-based flow recognition model (FA-ConFormer) is proposed, which utilizes deep networks to effectively extract dynamic frequency domain features from EEG signals and verifies its performance in recognizing various intensities and dynamic states of flow through algorithmic experiments. Finally, we implement an EEG-based visualization of the flow experience, presenting the dynamic changes in the flow states of the users during interaction from a process view, as illustrated in Fig.1.

The main contributions of this paper include:

- We describe dynamic states of flow experience from a process view and build the first multi-channel EEG dataset with labels of flow intensity and dynamic states.

- We propose FA-ConFormer, a frequency-aware convolutional Transformer to effectively recognize dynamic flow states and flow intensities based on EEG signals, which exhibits superior performance than previous methods.
- We achieve visualization of the dynamic flow experience for the first time, which provides an intuitive description of flow intensity and dynamic trends during the HCI activities.

2 RELATED WORK

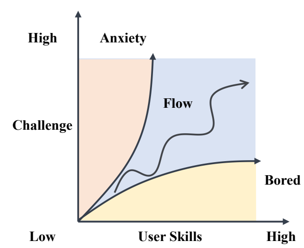
2.1 Dynamic Aspects of Flow

2.1.1 Dynamic Nature in the Concept of Flow. The flow experience is a dynamic process, and its state and intensity will change over time and in different situations [3]. Through long-term research, Csikszentmihalyi [19] found that the flow experience not only depends on the characteristics of the task itself but is also closely related to an individual's subjective feelings and the external environment. For example, in a study of musicians in professional classical orchestras, Cohen et al. [13] discovered that the flow state and intensity of musicians vary when they are faced with pieces of different difficulties.

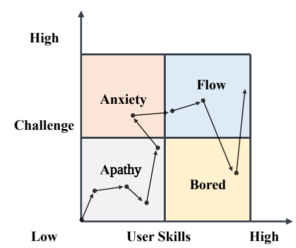
The generation and maintenance of the flow state rely on the dynamic balance between the task challenge and an individual's skills. When the challenge of a task matches an individual's skill level, the individual is more likely to enter a flow state. However, this balance is dynamic. Once the task difficulty suddenly increases and the individual's skills are insufficient to cope with it, or the task difficulty is too low and the individual's skills are excessive, the flow state will be disrupted. For instance, in the flow model proposed by Csikszentmihalyi et al. [15], when the task challenge is too high, the individual may feel anxious; when the task challenge is too low, the individual may feel bored.

The intensity of the flow is also dynamic, and it will change with the individual's level of engagement in the task, changes in their skill level, and the influence of the external environment. Dietrich et al. [23] pointed out that the intensity of the flow is closely related to an individual's neurocognitive mechanisms. When an individual is completely immersed in a task, the intensity of the flow will reach a relatively high level. In addition, the intensity of the flow is also affected by an individual's emotional state. For example, when an individual is in a positive emotional state, the intensity of the flow may be higher.

2.1.2 Dynamic Representation in Flow Models. The three-channel model is one of the most widely used theoretical frameworks in current flow research [10, 75]. This model posits that flow experiences arise from activities that present an optimal level of challenge and defines three flow-related states based on different conditions of challenge-skill matching, as illustrated in Fig.2a. When the level of task challenge exceeds the participant's skill level, individuals often experience stress and anxiety due to the high difficult task. Conversely, when the task challenge level is below the participant's skill level, the lack of sufficient challenge leads to boredom. The optimal flow experience occurs when the challenge level of the task aligns with the participant's skill level, creating an ideal task experience in this region known as the "flow channel". Building upon the three-channel model, researchers have developed a four-channel model, as shown in Fig.2b. This extended model asserts that flow experiences are only achieved when skills and challenges are matched at a higher level. At lower levels of matching, individuals experience a state of "apathy" rather than flow [24]. These models primarily emphasize the static dimensions of flow experience while providing a preliminary schematic of flow dynamics. In Figure 2, the arrows in the two models are not a representation of a certain mechanism, but rather a schematic illustration of the dynamics of flow. They visually demonstrate the dynamic changes of flow states, namely, the shifts in flow experience states triggered by continuous temporal changes in challenge-skill balance.



(a) Three-channel model



(b) Four-channel model

Figure 2: The three-channel and four-channel models illustrate the relationship among challenge level, skill level and flow state.

However, the above-mentioned models not fully focus on the dynamic aspects of the flow experience [6, 35]. Jenova Chen [11] proposed a player-centered Dynamic Difficulty Adjustment (DDA) game design methodology, emphasizing that by giving players the opportunity for subconscious choices, they can actively customize their gaming experiences and achieve dynamic difficulty adjustment. This dynamic adjustment mechanism fully reflects the dynamic nature of the flow experience, that is, the flow state is not a fixed one, but constantly changes with the interaction between individuals and the environment. It also verifies the importance of the dynamics of flow from a practical perspective. In addition, Kawabata [33] constructed an internal structure model of the flow experience, dividing the nine main components of the flow experience into proximal conditions and characteristics of the flow state, and hypothesizing a specific sequential relationship among various factors. These nine components include: clear goals, immediate feedback, balance between challenge and skill, concentration on the task at hand, sense of control, loss of self-consciousness, transformation of time perception, merging of action and awareness, and autotelic experience. Proximal conditions (e.g., clear goals, immediate feedback) lay the foundation for triggering flow, while characteristics of the flow state (e.g., loss of self-consciousness, transformation of time perception) emerge as the experience deepens. Individuals need to continuously adjust their states to maintain the flow experience according to the changing challenges and their own skill levels. Meanwhile, the various factors of the flow experience interact and change dynamically, which further illustrates the importance of verifying the dynamics of flow for in-depth research on the flow experience [4].

2.2 Methods for Assessing Flow

2.2.1 Subjective Measurement of Flow. Currently, the most popular tools for measuring flow are flow questionnaires and scales [29]. Commonly used flow measurement tools include the Game Experience Questionnaire (GEQ) [44], the Standard Game Flow Index (GFI) [8], the Flow State Scale (FSS), the Flow Measurement Scale [8], the Flow Experience Assessment Scale (FEAS) [75], and so on. However, the data obtained from these methods are based primarily on the overall subjective experiences of the participants.

The Experience Sampling Method (ESM) is a commonly used approach to measure flow experiences. It involves preparing a questionnaire with numerical scales and open-ended questions, which participants complete at regular intervals. ESM captures data on the frequency, location and content of activities in which individuals participate, as well as their perceived flow state. Researchers can use this information to explore and validate the components of the flow and identify activities that trigger this state [16]. However, ESM has a notable limitation: it measures flow at a macro-level over specific periods, lacking the precision needed to record the frequency and nature of flow experiences.

For these methods, the reliance on subjective reports can lead to insufficient accuracy and reliability with limited applicability to assess flow from a dynamic process view.

2.2.2 Neurophysiological Characteristics of Flow. Flow is not only a subjective experience, but it also has specific physiological response characteristics. Research indicates that flow is a positively valenced state (emotional component) in which people perceive current activity as optimally challenging (cognitive component) and are fully focused on the task at hand (behavioral component) [24]. Flow arises from the interaction between positive emotions and high attention, enabling individuals to meet increasing task demands with sustained efficiency without perceiving additional effort. Physiological indicators can be used to measure objective reductions in effort during flow [2, 22, 25, 45]. The existing literature indicates that various physiological metrics, including cortical activity, peripheral nervous system activity, cortisol secretion [34, 53], dopamine levels, and facial muscle activity, are related to flow states to varying degrees [20]. These physiological indicators reflect aspects of flow such as physiological arousal, positive valence, mental effort, and attention, thus directly or indirectly representing the flow state. In summary, neurophysiologically, flow is an effortless subjective or attentional state characterized by optimal physiological activation for completing the current task. This state is associated with reduced activation of the sympathetic and parasympathetic nervous systems [50].

Increasing research focuses further on the neural mechanisms and characteristics of brain activity linked to flow experiences. In flow states, individuals show transient hypofrontality, with implicit automatic processing dominating [23, 50, 59]. Empirical studies demonstrate that flow states are accompanied by significant increases in frontomedial theta wave power (reflecting enhanced attention concentration and executive control) and moderate alpha wave activity in the frontocentral region (corresponding to optimal cognitive efficiency) [40]. For instance, Katahira et al. [31] collected EEG data from participants during tennis matches and found that individuals in a flow state exhibited enhanced alpha activation in the right frontal cortex. Studies on the correlation between flow and EEG activity have revealed that compared to boredom, flow states show stronger theta wave activity in the frontal region [40]. Notably, further source localization analysis indicates that alpha/beta band power (BP) in the frontal lobe decreases during flow states, which further supports the mechanism of transient hypofrontality [41]. This transient hypofrontality of the prefrontal cortex is consistent with the "effortlessness" characteristic of flow, as reduced prefrontal involvement lessens conscious control, allowing for automatic and efficient task execution, and this process serves as the neural basis for maintaining the challenge - skill balance. Additionally, Hang et al. [26] confirmed a linear relationship between theta wave activity and subjective flow ratings in a single channel prefrontal EEG study, emphasizing the correlation between frequency domain features and flow intensity. Indices such as power spectral density (PSD) and differential entropy (DE) can sensitively reflect changes in the energy distribution of alpha/beta oscillations [20]. These findings collectively indicate that transient hypofrontality, enhanced frontal theta wave activity, and balanced frontocentral alpha wave activity provide core neural characteristic support for the dynamic regulation of challenge - skill balance in flow states.

2.3 Methods for Calculating Flow

According to the neurophysiological mechanism of flow, researchers have explored objective methods to assess flow based on physiological data, especially EEG data [38, 64].

2.3.1 Flow Calculation Based on Multiple Physiological Signals. Using statistical methods, Harmat et al. [27] distinguish between flow and non-flow states based on a custom-built database containing ECG and respiratory signals, demonstrating the feasibility of using physiological signals to differentiate flow states. Sinha et al. [65] collected EEG, heart rate variability (HRV), and galvanic skin response (GSR) data using wearable devices, and applied a Markov chain model to differentiate between flow and boredom states using a modified Stroop test. This validated the feasibility of detecting flow experience through physiological responses.

By combining feature selection methods with machine learning algorithms, Ye et al. [75] addressed the high spatial and temporal resolution of physiological signal data and the issue of feature redundancy. They compared five classification models to detect flow, including support vector machines, decision trees, logistic regression, naive Bayes, and random forests. The highest classification accuracies on three datasets were 60%, 66% and 45%, respectively. After applying standardization strategies, the highest accuracies for the three datasets increased to 76%, 82% and 71%, respectively.

Based on deep learning, Marco et al. [44] proposed the DeepLow model to distinguish flow states. This method uses wristband devices to collect physiological signals and applies end-to-end deep learning to detect flow states. It differentiates between high-flow and low-flow states and detects boredom and stress, achieving 70% accuracy.

2.3.2 *Flow Calculation Based on EEG Signals.*

In the early exploration, researchers used statistical analysis methods to verify whether EEG signals could be effectively used to detect flow states. Plotniko et al. [58] established a database of EEG data collected from electrodes and calculated the power within a 1-second sliding window to detect flow states. Katahira et al. [31] collected EEG signals from 16 participants using a PD device during a mental arithmetic game and employed analysis of variance (ANOVA) to successfully differentiate between boredom, flow, and mental overload states, strongly demonstrating that EEG can be used to distinguish game experience states. Wang et al. [72] extracted EEG information through learning tests and wearable devices and also used ANOVA to distinguish between boredom and flow states.

With the advancement of research, machine learning algorithms were introduced into EEG data processing, aiming to classify flow-related states and optimize data features. Chanel et al. [7] applied three classifiers-linear discriminant analysis, quadratic discriminant analysis, and support vector machines with a radial basis function kernel-to an EEG dataset to classify boredom, satisfaction (flow), and anxiety states. The results showed that linear discriminant analysis and support vector machines with a radial basis function kernel performed best, with accuracies of 49% and 47% respectively. After using the FCBF feature selection method, the accuracy of quadratic discriminant analysis for peripheral features increased to 59%, and ANOVA feature selection increased the accuracy of linear discriminant analysis to 56%.

In recent years, deep learning models have demonstrated great advantages in EEG-based flow state detection, being able to more accurately decode flow states and extract complex features. Cherep et al. [12] used EEG headsets to collect data and applied the deep learning model EEGnet to decode flow states, focusing on power changes in local brain regions and the coordination between brain areas. The accuracy of this method in distinguishing between boredom, flow, and overload states exceeded 65%. Song et al. [66] proposed the EEG Conformer model, which extracts both local and global features within a single EEG classification framework. By learning local features through one-dimensional convolution and capturing correlations between local time features through self-attention mechanisms, it achieved state-of-the-art performance on three public EEG datasets.

Although existing models can detect flow states through EEG signals, there are obvious deficiencies in analyzing the dynamic states of flow. On the one hand, there is a lack of an EEG database that describes the dynamic states of flow experiences from a process view. On the other hand, the technology for extracting dynamic frequency domain features is still immature. Existing methods often focus on simple measurements, such as the energy intensity in specific frequency bands. Although intuitive, they are difficult to capture deeper and more nuanced frequency domain dynamic changes, such as complex inter-band interactions, non-linear evolution trends, and subtle time-frequency changes. These limitations affect the accuracy of dynamic flow state recognition and hinder a detailed portrayal of users' true flow experiences. To fill these gaps, this study will construct the first EEG dataset that describes the dynamic changes in the flow process from a process view. The next section will introduce the development of experimental tasks for inducing dynamic flow states.

3 TASK OF INDUCING FLOW EXPERIENCE

Previous research on flow has often focused on distinguishing between flow and non-flow states, without delving into the dynamic changes within the flow state itself [39, 55]. In this study, we designed an HCI task to induce different dynamic states and intensities of flow experience. During the experimental task, participants are multiply sampled to report the current flow state and intensity, so as to record the changes of flow at different time points in detail, which is helpful to in-depth understanding of the dynamic flow states from a process view.

3.1 Design Principles

To construct an effective task for inducing flow, we considered a variety of game activities, including "Whac-A-Mole", "Tetris" et al. [27, 75, 76], and referenced studies on the emotional and physiological aspects of these games [50, 51, 72]. According to the research purpose, the selection criteria of the task were as follows:

- The game should better be well-known to avoid adding additional cognitive load to the participants.
- The experimental task should be straightforward, with simple and easy-to-learn operations.
- The difficulty of the experimental task should be easily adjustable to accommodate testers of varying skill levels.
- The duration of the experimental task should be reasonable and offer some flexibility.
- The game should maintain a seamless operational flow, unaffected by uncontrollable difficulties (e.g., Unlike the game of Tetris, where misplacing a block can lead to an uncontrollable increase in difficulty. This not only disrupts the delicate balance of challenge manipulation within the game but also undermines the fluidity of participants' actions, as the unexpected rise in complexity can quickly derail the smooth progression of their gameplay strategies.)

After a comprehensive comparison of existing tasks, we decided to design a task based on the "Whac-A-Mole" game, which has been demonstrated to be effective in inducing different flow states [75, 76]. It involves targeting and hitting a certain number of monsters or moles, with challenge level adjustment made by varying the number and frequency of appearances of these targets. It can well meet the above criteria, and thus was chosen by this study to induce flow experience.

3.2 Task Goal

Previous research has indicated that the use of themes and narratives can enhance the degree of engagement and presence of participants [1, 5, 52]. Based on the storyline of a two-user version of the "Whac-A-Mole" game for the induction of flow [76], we developed a single-user version and designed the storyline as follows: "You run a farm that produces and sells vegetables and other crops. A group of moles is trying to steal your products, and you need to protect your crops and fight off the moles to maximize your profit." Consequently, the task goal of the participants is to achieve higher profit score as much as possible. The score depends on the number of moles that have been successfully hit by the participants.

3.3 Difficulty Adjustment

Based on the flow channel model 2, achieving flow experience requires a balance between the individual's skill and the challenge level of task [15, 75]. Therefore, the flow-inducing task should support participants to adjust the task difficulty according to their own skill. Note that dynamic flow does not assume that the task is inherently dynamic. Rather, controlled difficulty modulation serves as an experimental lever to enhance flow occurrence efficiency. In this game, four moles appear each time and their escape speed can be set at five levels. Participants are allowed to quickly adjust the task difficulty once every one-minute interval to achieve an optimal task-difficulty balance.

3.4 Game Interaction and Feedback

The participants need to use the mouse to click on the moles appearing on the screen. The game interface shows the task difficulty, task countdown and real-time score in the upper right corner. The "Whac-A-Mole" game interface is shown in Fig.3b.

3.5 Sampling Method

Unlike most previous studies which measured flow experience only once after the task, this research is to capture more immediate and dynamic instances of flow states. Referring to the Experience Sampling Method [54], we sampled the flow experience multiple times during the task. In this study, each round of the game lasts 5 minutes. During the game, the participant experience is sampled every minute, as shown in Fig.3c and Fig.3d (5 samples per round). When each sample is conducted, an evaluation interface is designed to pop out and ask participants to score the dynamic states and perceived intensity of flow, then adjust the task difficulty. Specifically, the dynamic states (e.g., upgoing, downgoing) being scored correspond to the transition dimension, which describes directional changes between flow states, while the perceived intensity ratings reflect the progression dimension, capturing the onset, development, peak, or decline of flow intensity over time. We adopt the following measures to ensure the validity of sampling data:

- To ensure that participants fully understand the concept of flow experience before entering the game, a detailed description of the concept and examples will be given to them.
- As for dynamic flow states, this study defines five states (no flow, low state, high state, upgoing, and downgoing) and designed a brief scale to report them (Fig.3c).
- In terms of flow intensity, the use of the flow questionnaire with multiple items will break the continuity of participants' flow state and decrease the validity of the measurement [56]. To minimize disruption, this study used a single-item measure to measure the flow intensity [36, 76]. The item was developed from Csikszentmihalyi's flow questionnaire [54, 60] by Zhang et al. [76], scoring on a Likert scale ranging from 0 (no flow) to 3 (high flow) (see Fig. 3d).
- To minimize disruption to the continuity of the game experience, the game scene remains visible when the evaluation interface appears. Fig.3c shows the interface.
- To further ensure the effectiveness of the single-item measure in experience sampling, a rate-rerate method is adopted to minimize the potential measurement error [21]. Specifically, this study requires participants to review the recorded video immediately after completing the task to verify the accuracy of the scoring. Participants are asked to review each sampling moment (aligned with the timestamps in the video) and confirm or revise their initial ratings. This process allows participants to contextualize their initial judgments with the actual task progression, enhancing the reliability of the flow labels.

4 DATASET CONSTRUCTION

4.1 EEG Data Collection

4.1.1 Participants. The experimental data was collected from 94 volunteers (18-50 years) recruited from a local university. The participants were all in good health, without a history of neurological disorders, and had a comprehensive understanding of the tasks. None of the participants experienced alcohol consumption, excessive fatigue, medication use, or illness before the experiment. The study was conducted in accordance with the guidelines of the Declaration of Helsinki and approved by the Human Research Ethics Committee of Shandong University. Informed consent was obtained from each participant.

4.1.2 Data Collection Devices and Environment. In the study of flow state recognition based on physiological signals, various EEG recording devices are available. To minimize discomfort from wearing device interfere the flow experience, we selected a portable EEG device for data collection.

During the experiment, we used the EMotiv Epoc X, a lightweight head-mounted device, to record multi-channel EEG signals. Epoc X is equipped with 14 EEG sensors and 2 reference sensors, with a sampling rate of 256Hz. The electrode placement follows the 10-20 international system, including channels AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4 [43], as shown in Fig.3a. We selected the Emotiv Epoc X due to its ease of use, practicality, and minimal physical constraints. It has also been used effectively in the building of high-quality EEG datasets related to flow experience and emotions [32, 46, 57, 69, 77]. To balance the device's portability (critical for maintaining a natural flow experience) with the signal quality requirements for accurate flow state analysis, we implemented movement restrictions during data collection to minimize motion artifacts in EEG signals and applied Independent Component Analysis (ICA) to further remove residual noise.

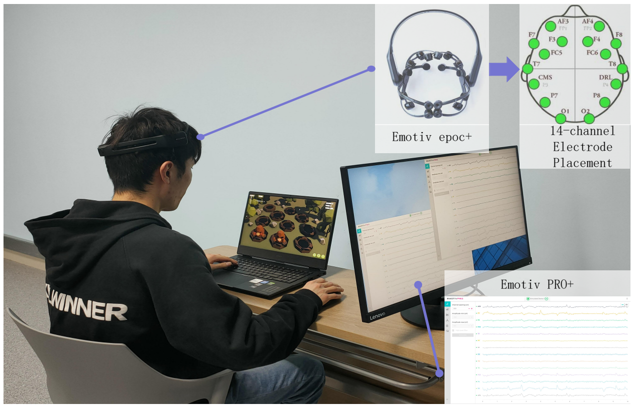
4.1.3 EEG Data Collection Process. The EEG data collection process is illustrated in Fig.4. It includes two phases.

(1) Phase 1: Preparation

We first introduced to the participants the concepts related to the flow experience and ensured that they fully understood them. Then, we introduced to the participants the experimental task, the objectives, and the operational method and ensured that they fully understood how to perform the task. Next, they completed a questionnaire to collect demographic information. after that, they were fitted with EEG signal collection equipment.

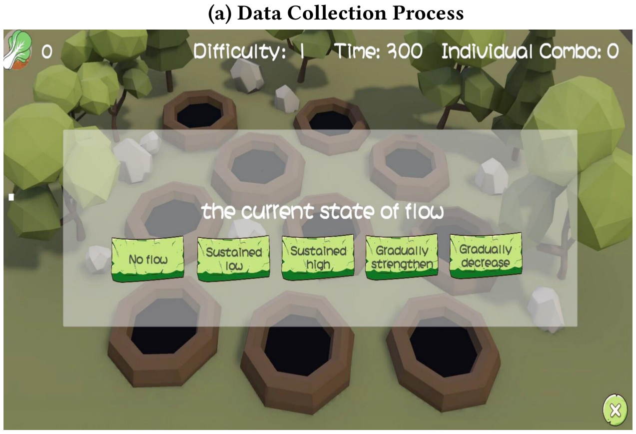
(2) Phase 2: Data Collection

In the second stage, data collection is carried out as follows:



(a) Data Collection Process

(b) Game Interface



(c) Flow State Selection

(d) Flow Intensity Selection

Figure 3: EEG signal data collection and game scenarios: (a) shows the brain signal setup with 14 EEG channels marked; (b) presents the game start screen; (c) depicts the flow state selection; (d) displays the flow intensity interface.

Participants were required to sit and relax for three minutes to stabilize their physiological indicators to baseline levels, facilitating the calculation of baseline EEG values for subsequent experiments.

After the rest period, participants went to the game phase and played three rounds of the game task. The starting difficulty levels for the three rounds were varied to capture various dynamic flow states. As introduced in Section 3.5, flow experiences were sampled during this period.

The researchers monitored the EEG data of the participants during each game session individually. Any anomalies in the signals were recorded and considered for exclusion from the subsequent analysis. The EEG data collection process for each participant took approximately 30-40 minutes. Finally, the EEG samples were labeled and prepared based on flow scores obtained from the participant experience sampling, facilitating the organization of the dataset for further analysis. Fig.3a illustrates the EEG data collection process.

Currently, there is still no completely interference-free method. To minimize interference during data collection, we highlighted several design principles in Section 3.1. Moreover, the "Whac-A-Mole" task paradigm used in this paper has been proven effective in maintaining flow continuity during one-minute sampling interval [76]. Post-hoc video reviews indicated that participants did not perceive notable interference throughout the sampling process.

4.2 Dataset Organization

In this study, the reasonable organization of the dataset is of great significance for the accurate analysis and mining of information related to the participants' states. We started with the raw 14-channel EEG data obtained from the Emotiv Epoc X device and gradually carried out a series of rigorous and systematic data processing procedures. The aim is to construct a high-quality and representative dataset, which lays a solid foundation for the subsequent in-depth research.

- **EEG Signal Segments**. The raw 14-channel EEG data (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4) obtained from the Emotiv Epoc X were saved in EDF format and pre-processed using the EEGLAB toolbox. Initially, raw data were imported and electrode positioning was carefully verified to ensure accurate signal capture. The data were then re-referenced to the average reference to standardize the recordings.

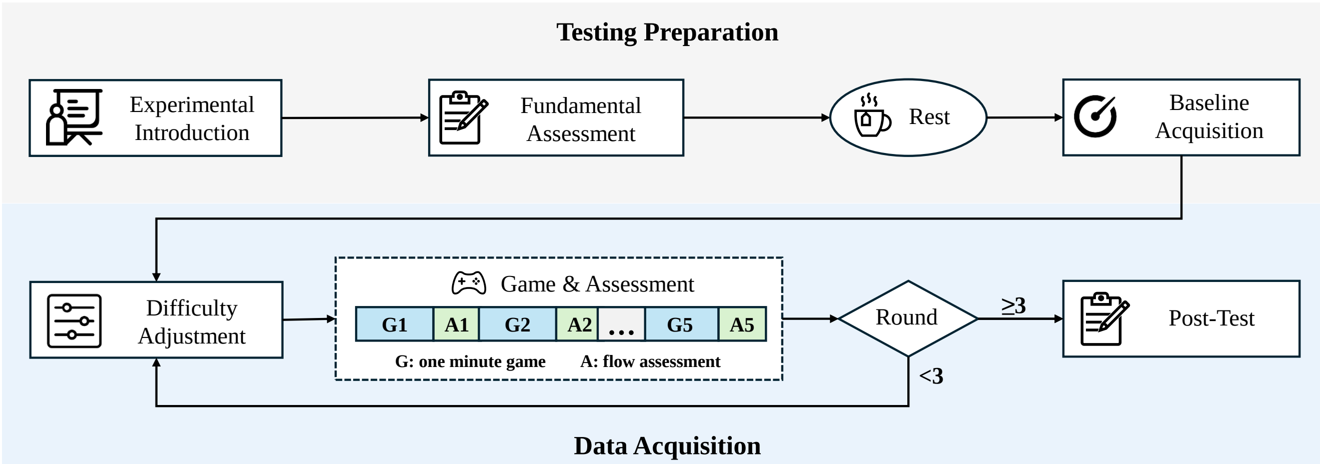


Figure 4: The data collection flowchart includes the Testing Preparation Phase and the Data Collection Phase. Each participant is required to complete three rounds of the game and choose their current flow state and intensity in each round.

- **Filtering and Nromalization**. Filtering was performed to remove specific frequency interferences, with a bandpass filter applied between 1 Hz and 50 Hz using a 4th order Butterworth filter [27]. Each data set was subsequently segmented into 1-minute intervals to align with the timing of the flow ratings of the participants. This process resulted in a series of data segments, each corresponding to a specific flow rating moment. In addition, Z-score normalization and non-overlapping sliding windows of size 256 are applied in the training pipeline to reduce volatility and non-stationarity.
- **Dataset Composition**. Further prepossessing involved EEG signal decomposition and removal of eye movements, including ICA and detection of eye movements artifacts, implemented using specialized EEGLAB plugins and custom scripts. Operations of translating and scaling the samples are also performed to augment the samples for class balancing. The final dataset comprises 94 usable samples, each representing three experimental sessions per participant. It includes flow label information (flow intensity and state, labels selected by the participants and system), timestamps (game start, experience sampling, and game end), and EEG data from 14 channels per minute of each session. Participants were recruited across various age groups to ensure the diversity and representativeness of the dataset.

The dataset of this paper is released at : https://drive.google.com/drive/folders/1IFO6BrsaMI112sd793-t27_s8Fsglc7Q?usp=drive_link. Detailed information about the data is also summarized in the "Readme.txt".

5 FLOW RECOGNITION BASED ON FREQUENCY AWARE CONVOLUTIONAL TRANSFORMER

To address the challenges of representing temporal variations in EEG signals and the complex inter-channel relationships when recognizing flow experience, this paper introduces FA-ConFormer, a method that leverages frequency domain density representations combined with cross-channel convolutions and global attention fusion to produce flow state recognition results, including the intensity of flow and its temporal dynamics. As illustrated in Fig.5, the FA-ConFormer captures microstate transitions, complementing minute-level subjective scores to enable "macroscopic trend-microscopic feature" analysis. FA-ConFormer consists of three primary modules: In the **frequency representation module**, the micro-differential entropy and PSD are calculated from the EEG signal samples to extract key frequency domain features for each channel. The **cross-channel fusion module** then integrates information across channels and features through convolution operations. In the **global attentive learning module**, the fused features along with the classification tokens are fed into a lightweight five-layer Transformer network, where the information in the global frequency domain is integrated through attention mechanisms, before being passed to linear classifiers for identifying the flow intensity and flow states.

5.1 Frequency Representation

The selection of frequency-domain EEG features is grounded in the neurocognitive mechanisms underlying flow experiences and is consistent with tenets of flow theory as well as cognitive models such as transient hypofrontality.

We chose the θ (4–7Hz), α (8–12Hz) β (13–30Hz), and γ (31–50Hz) bands' PSD and BP to capture complementary aspects of flow dynamics. For instance, θ band activity has been closely linked to heightened attentional focus and executive control—hallmarks of the flow state. An increase in prefrontal θ band power (indexed by BP_θ) directly corresponds to the deep concentration described by flow theory, during which an individual can sustain continuous task engagement. α band activity, quantified via BP_α, reflects optimal cognitive efficiency and emotional stability. Moderate α oscillations in prefrontal and central regions (as measured by PSD) align with the "challenge–skill balance" core to flow, in which task demands match individual capabilities. This balance minimizes cognitive dissonance and enables the effortless immersion characteristic of flow.

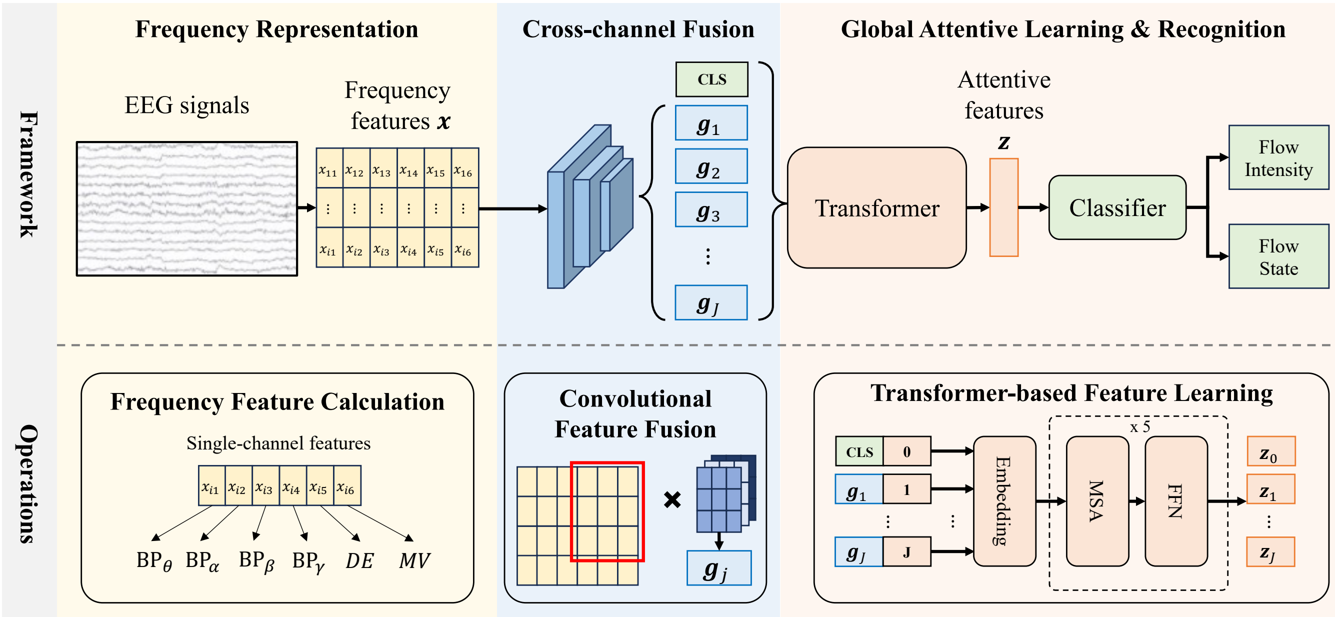


Figure 5: Illustration of FA-ConFormer, which integrates frequency domain features through a convolutional network and implements attentive learning based on a Transformer, thereby achieving the classification of flow intensity and state from EEG signals.

We also include DE to index signal complexity, which decreases in flow due to more regularized neural activity (e.g., synchronous θ oscillations). This reduction in complexity embodies the "ordered consciousness" feature of flow, wherein cognitive resources are allocated efficiently without extraneous interference. In addition, mean value (MV) provides a baseline reference, highlighting deviations associated with flow onset (e.g., the shift from resting-state α dominance to task-relevant θ engagement).

To better describe the processing of our method, we discretely form EEG signals as a 2D matrix $\mathbf{A} = \{a_{m,n} | m = 1, ..., M; n = 1, ..., N\}$, where M indicates the number of channels, and N is the number of sampling steps. To obtain a frequency domain representation, the data of each channel is first transformed by a discrete Fourier transformation:

$$F(i,m) = \textstyle\sum_{n=1}^{N} a_{m,n} \cdot e^{-2\pi n \frac{i}{N}} \tag{1}$$

where i is the frequency index and e is the base of the natural logarithm.

Additionally, to extract the representation in the frequency domain, we computed the power spectrum $P_m(f)$ and PSD:

$$P_m(f) = \frac{1}{N}\left(|F(i,m)|^2 + |F(N-i,m)|^2\right) \tag{2}$$

$$\mathrm{PSD}(f) = \frac{1}{M}\sum_{m=1}^{M} P_m(f) \tag{3}$$

where f is the frequency value associated with i.

Considering the characteristics of different frequency bands of PSD, we combined the signals of $\theta(4Hz \le f \le 7Hz)$, $\alpha(8Hz \le f \le 12Hz)$, $\beta(13Hz \le f \le 30Hz)$, and $\gamma(31Hz \le f \le 50Hz)$ bands to obtain the BP:

$$BP = \frac{1}{|B|}\sum_{f \in B} \mathrm{PSD}(f) \tag{4}$$

where B is the frequency index satisfying $f_{start} \le f \le f_{end}$.

The aforementioned features indicate details like density and energy in the frequency domain, where as the DE can reveal hidden attributes especially in the analysis of non-stationary, nonlinear, or intricate signals. The formula for calculating DE is as follows:

$$DE = \log(2\pi e \sigma^2/2) \tag{5}$$

where σ^2 is the variance of $a_{m,n}$.

Finally, MV of the matrix are combined in to the features:

$$MV = \frac{1}{N}\sum_{i=1}^{N} a_{m,n} \tag{6}$$

5.2 Cross-channel Convolutional Fusion

The cross-channel convolutional fusion mechanism is designed to emulate the inter-regional neural co-activation characteristic of flow states as described by flow theory. Flow experiences depend on the synchronized activity of distributed cortical areas—for example, prefrontal regions that regulate attentional control and parietal regions that integrate multisensory input. By capturing local neighborhood dependencies among EEG channels and simulating functional connectivity between distinct brain regions during flow, this mechanism supports the integration of information across regions to sustain global task engagement. It addresses a key limitation of conventional approaches, which often overlook such global dynamics, by enhancing sensitivity to subtle inter-channel interactions and extracting multi-scale patterns (e.g., cross-channel α/β balance) critical for discriminating dynamic flow sub-states like upgoing and downgoing.

To implement this mechanism, the frequency representation module first extracts features including $BP_\theta, BP_\alpha, BP_\beta, BP_\gamma, MV$ and DE from 14 channels. We rearrange these features into a matrix $\mathbf{x} = \{x_{i,j}|i = 1, ..., 14; j = 1, ..., 6\}$. The $\mathbf{x}$ encodes frequency information in EEG signals, and to enhance the fusion among channels, we introduce a convolutional layer to further fuse features.

The convolutional layer integrates information within a neighborhood by sliding a convolution kernel across the input. Utilizing multiple convolution kernels allows for the extraction of various features from the input. The process of convolution operation $Conv(.)$ is formulated as:

$$\mathbf{g} = Conv(\mathbf{x}) \tag{7}$$

where the fuse features $\mathbf{g} = \{g_1, ..., g_J\}$.

5.3 Global Attentive Learning for Flow Recognition

The design of the Global Attentive Learning Module is highly aligned with the neurocognitive mechanisms of flow, particularly echoing the core role of the prefrontal cortex in top-down attentional control. According to flow theory, in a flow state, the prefrontal cortex sustains immersive engagement by integrating information across time and cortical regions, coordinating global attention. The Global Attentive Learning Module in FA-ConFormer precisely simulates this mechanism: it incorporates a five-layer Transformer, which captures long-range temporal dependencies and cross-channel correlations in EEG signals through the introduction of a [CLS] classification token and multi-head self-attention (MSA) mechanism, thereby integrating global frequency dynamics (e.g., the time-varying interaction between α/θ bands) — this is consistent with the function of the prefrontal cortex in filtering irrelevant stimuli and prioritizing task-relevant information during flow states. Subsequent feed-forward networks (FFNs) and layer normalization further reinforce key features (such as bursts of θ band activity associated with peak flow intensity), embodying the "automaticity" characteristic of flow (efficient allocation of cognitive resources without deliberate effort). This architectural design enables the model to accurately predict dynamic flow sub-states (e.g., upgoing).

5.3.1 Transformer-based Feature Learning. The matrix $\mathbf{g}$ contains varies local information of EEG signals, so in the global attentive learning module, we design a five-layer Transformer for learning the global information. It adds a class token [CLS] to the input $\mathbf{g}$, and the new input sequence is $\{[CLS], \mathbf{g}_1, ..., \mathbf{g}_J\}$.

The Transformer block consists of two main components: a MSA and a FFN, each previously connected to a Layer Normalization. Each multi-layer perception layer (MLP) consists of two 2048-dim fully connected layers, with a dropout layer behind it. The activation function used in this paper is GeLu. The Transformer block can be described as:

Table 1: Parameter settings of FA-ConFormer

Module	Hyperparameter	Value
Feature Extraction	Input Dimension	14
	Padding Type	same
Convolutional Layer	Stride Size	1
	Kernel Size	3
	Model Dimension	128
	Number of Heads	8
Transformer Encoder	Number of Layers	5
	Dropout Rate	0.1
	Dimension of Feedforward	2048
Classifier	Number of Flow Intensity	4
	Number of Flow state	5

$$\mathbf{z}_{l+1} = \text{FFN}^l(\text{MSA}^l(\mathbf{z}_l)) + \mathbf{z}_l \tag{8}$$

where $\mathbf{z}$ is the attentive features, and the index of Transformer block is $l = 1, ..., 5$.

5.3.2 Classifier. After feature extraction, the linear classifiers task the first token of $\mathbf{z}$ as input, simultaneously generating flow state $\mathbf{P}_{st}$ and flow intensity $\mathbf{P}_{in}$. We use cross-entropy as the recognition loss during the training.

6 EXPERIMENTS

6.1 Experimental Setup

In this paper, the whole dataset is divided into training set, validation set and test set, the proportions are 80%, 10% and 10%, respectively. The models in this experiment are implemented based on Pytorch. During training, the batch size is set to 32, the optimizer is Adam, and the initial learning rate is 1e-4 training for 100 epochs. The loss function in this experiment is cross-entropy loss, which can be formulated as

$$L = -\sum y_i \log p_i \tag{9}$$

where L is the value of the cross-entropy loss function, y_i is the ground-truth label, p_i is the predicted probability of the model for a single output. Finally, this experiment iteratively optimizes the model parameters through multiple training cycles while monitoring the loss value during training.

In the recognition of flow state and flow intensity, Precision, Recall, F1-score and Accuracy were adopted in this paper to comprehensively evaluate the performance of different classifiers on flow intensity and flow state recognition tasks. Accuracy reflects the proportion of samples that the classifier correctly identifies as positive, while recall measures the classifier's ability to identify all actual positive samples. The F1 score serves as a harmonic average of accuracy and recall, providing a single performance metric that balances the two. Finally, accuracy represents the ability of the classifier as a whole to correctly predict the sample. Table 1 lists the parameters for identifying the flow state.

6.2 Performance Comparison

In order to comprehensively evaluate the effectiveness of the proposed model, we selected widely used models in the field of flow recognition as benchmarks for performance comparison, including K-Nearest Neighbors (KNN) and Support Vector Machines (SVM), which showed flexibility in EEG recognition [42, 74]. In addition, advanced deep learning methods are also compared, including Convolutional Neural Network combined with Long Short-Term Memory (CNN-LSTM) [49], and Transformer-based models [66, 67, 71].

6.2.1 Results of Flow Intense Recognition. The experimental results on the flow intensity recognition task are shown in Table 2, from which we can observe:

- **The FA-ConFormer model demonstrates a significant advantage in the recognition of flow intensity, particularly in terms of precision and accuracy, showing a high recognition capability.** The FA-ConFormer model achieved a precision of 77% and an accuracy of 71% in the recognition of flow intensity. This performance is notably superior to that of traditional machine learning models such as SVM, which recorded a precision of 44% and an accuracy of 44%, and even exceeds that of deep learning models such as EEG Conformer, which attained a precision of 71% and an accuracy of 68%. The FA-ConFormer model optimizes the extraction of frequency domain features through its advanced architecture, which compared to the simple feature extraction methods of traditional models, can more accurately reflect the subtle changes indicative of the flow state.
- **The FA-ConFormer model demonstrates improved balance and robustness in the multitask classification of flow intensity, effectively discriminating among various flow intensity categories.** In multi-classification tasks for flow intensity, the FA-ConFormer model achieved an F1 score of 74%, surpassing the 45% of SVM and 67% of EEG Conformer. This performance highlights the strength of FA-ConFormer in managing imbalanced datasets. The model's advanced features, such as positional coding and multi-head self-attention, enhance its ability to interpret EEG signal time series and consider multiple signal features simultaneously. These contribute to its improved sensitivity and accuracy in recognizing flow intensity classes.
- **The FA-ConFormer model exhibits a high recall rate, facilitating the comprehensive identification of all flow intensity levels and minimizing omissions, which is essential for real-time monitoring and responsiveness to participant states.** The FA-ConFormer model excels in the recognition of flow intensity, especially with complex data, achieving a 70% recall rate compared to 46% for SVM and 62% for EEG Conformer. Its architecture, which combines deep convolutional layers with the Transformer, effectively processes both spatial and temporal features of EEG signals. This dual approach to data fusion significantly boosts recall, ensuring comprehensive identification of flow intensity states and minimizing missed detections. This performance is crucial for real-time applications that require prompt detection and response to participant states.

6.2.2 Results of Flow State Recognition. The experiment also provides the results of flow state recognition. Table 3 lists in detail the performance indicators of each classifier in the task of flow intensity recognition.

Table 2: The flow intensity recognition results of different classifiers

Model	Precision	Recall	F1-score	Accuracy
KNN	0.40	0.44	0.42	0.48
SVM	0.44	0.46	0.45	0.44
CNN-LSTM	0.40	0.43	0.41	0.47
Transformer	0.43	0.54	0.48	0.53
MAFormer	0.58	0.64	0.60	0.61
MV-Transformer	0.57	0.67	0.61	0.64
EEG Conformer	0.71	0.62	0.67	0.68
FA-ConFormer	**0.77**	**0.70**	**0.74**	**0.71**

- **The FA-ConFormer model achieves superior precision and accuracy in the domain of flow state recognition.** In the field of flow state recognition, the FA-ConFormer model has shown exceptional performance, with precision and accuracy rates of 72% and 68%, respectively. These figures exceed the 40% precision and 46% accuracy of traditional machine learning models like SVM, as well as the 70% precision and 65% accuracy of the EEG Conformer model. The FA-ConFormer model's architecture, which fuses deep convolutional layers with a Transformer encoder, is adept at handling sequential EEG data, capturing intricate patterns and fluctuations, thereby enhancing the precision and accuracy of flow state recognition for real-world applications.
- **The FA-ConFormer model exhibits exceptional comprehensive performance in flow state recognition, particularly in the recognition of dynamic changes in flow states.** The FA-ConFormer model excels in the recognition of flow state, achieving an F1 score of 68%, surpassing 47% of the SVM and 65% of the EEG conformer model. Its advantage lies in the multi-head self-attention mechanism, which provides heightened sensitivity to flow state changes, especially during transitions. This precision is vital for accurate flow state recognition, underscoring the FA-ConFormer model's effectiveness in scenarios demanding sensitive state transition detection.
- **In comparison to the FA-ConFormer model, traditional models such as SVM exhibit reduced efficacy in flow state recognition.** In the field of flow state recognition, traditional machine learning models such as SVM show a recall rate of only 45%, behind the 65% of the FA-ConFormer model. This indicates that traditional models struggle to capture nuanced changes in the EEG data, which are critical for recognizing flow states. Their reliance on manual feature extraction is insufficient for the complex and high-dimensional nature of EEG signals, especially during dynamic state transitions. Advanced models like FA-ConFormer, with their sophisticated analytical capabilities, are better equipped to handle the intricacies of EEG data analysis, making them more effective for flow state recognition tasks.

- **The performance of the flow intensity recognition task is generally better than that of the flow state recognition task.** It may be due to the fact that the flow state recognition involves a more detailed classification, leading to the reduction of various indicators, such as the accuracy of flow recognition.

Table 3: Flow state recognition results of different classifiers

Model	Precision	Recall	F1-score	Accuracy
KNN	0.46	0.42	0.44	0.44
SVM	0.40	0.45	0.47	0.46
CNN-LSTM	0.45	0.40	0.42	0.43
Transformer	0.58	0.48	0.52	0.56
MAFormer	0.60	0.50	0.55	0.59
MV-Transformer	0.65	0.55	0.60	0.62
EEG Conformer	0.70	0.60	0.65	0.65
FA-ConFormer	**0.72**	**0.65**	**0.68**	**0.68**

To ensure the stability and reliability of the model performance:

- The performance plots of the model under 5 random seeds demonstrate that FA-ConFormer stably outperforms EEG Conformer in precision, recall, F1-score, and accuracy, with smaller performance fluctuations, reflecting stronger robustness.
- This study employed a ten-fold cross-validation strategy on the dataset, with the results as follows: In flow intensity recognition, FA-ConFormer achieved a precision of 0.7072±0.0132, which is approximately 7.5% higher than that of EEG Conformer (0.6578±0.0198). In flow state recognition, its precision reached 0.6878±0.0100, showing an approximately 6.2% improvement compared to EEG Conformer (0.6476±0.0177). Additionally, FA-ConFormer outperformed EEG Conformer and other comparative models in indicators such as recall and F1-score across both tasks, verifying its excellent classification performance and generalization ability. The results of leave-one-out cross-validation show that in both flow intensity and state recognition, FA-ConFormer outperforms Transformer and EEG Conformer in indicators such as precision and recall, demonstrating better adaptability to data with individual differences.
- The results of the permutation test (10,000 permutations) show that two-tailed p-values for all indicators in flow intensity/state recognition were all < 0.001, indicating highly significant differences. The Bootstrap confidence intervals (10,000 samplings) for mean differences (e.g., [0.0346, 0.0641] for flow intensity precision) do not contain 0, confirming the reliability of the differences. Cohen's d effect sizes (e.g., 8.9437 for flow state recall) are all much greater than 0.8, indicating a "large effect," which means the advantages of FA-ConFormer are significant and practically meaningful.

All these results are provided in the Appendix.

6.3 Visualization Analysis of Flow Intensity and Flow States

In this section, our goal is to visualize the changes in flow states during gameplay and their relationship with psychological states. To clearly present the various stages of the flow, we visualized the data using line graphs and bar charts. The line graph represents the flow intensity, which is divided into four levels: no flow, low flow, medium flow, and high flow (levels 0 to 3). The bar chart uses different colors to indicate the changes in flow states: gray (no flow), red (maintain low state), blue (maintain high state), green (upgoing), and orange (downgoing). These visualization figures are expected to help researchers enable flow-state analysis, support adaptive interface design, and facilitate users to better understand the dynamic changes of their flow intensity and flow states.

Specifically, we first utilized the FA-ConFormer model based on EEG signals to obtain the flow state data of each participant during the game. Then, we selected data from different participants with similar flow intensity variations over three game rounds to ensure a comprehensive analysis of the changes in flow states. To enhance the stability and interpretability of the data, we applied a median filter with a window size of 5 to the predicted results.

6.3.1 Analyzing the Depiction of Variations in Flow State Intensity. In the visualization process, we analyzed data from different participants across three rounds of the game. According to Fig.6, when the flow intensity is generally high (mainly between 2 and 3), there are more frequent and longer periods of high-flow states. In contrast, when the flow intensity is lower (mainly between 1 and 2), there are more frequent and longer periods of low-flow states.

- Sustained High-flow State: For Fig.6(a) and Fig.6(b), it can be observed that when the flow state shows an upward trend (green), the flow intensity typically increases or is expected to increase shortly thereafter. This suggests that changes in flow state may serve as a predictor for variations in flow intensity. Additionally, the results indicate that under high-flow conditions, participants' experiences of increased flow states are more consistent with changes in flow intensity. This implies that, under high-flow conditions, participants are more sensitive to changes in flow states. In contrast, when the flow state declines, participants may be less sensitive to the differences between declining states and low-flow states.
- Sustained Low-flow State: In contrast, for Fig.6(c) and Fig.6(d), it can be observed that the two cases predominantly exhibit a low-flow state (red), with overall lower intensity. Unlike high-flow states where increases in the flow state were predictive of rising intensity, changes in flow state during low-flow states do not consistently align with changes in intensity. This may be because the sensitivity to flow state fluctuations appears to be reduced in low-flow states.Specifically, the low-flow state itself has inherent instability characteristics, making it difficult to present a stable corresponding pattern between the state and intensity changes. Meanwhile, when humans are in a low-flow state, their perceptual sensitivity to their own flow fluctuations diminishes. It becomes rather challenging to accurately capture the association between the state and intensity, thus resulting in inconsistent

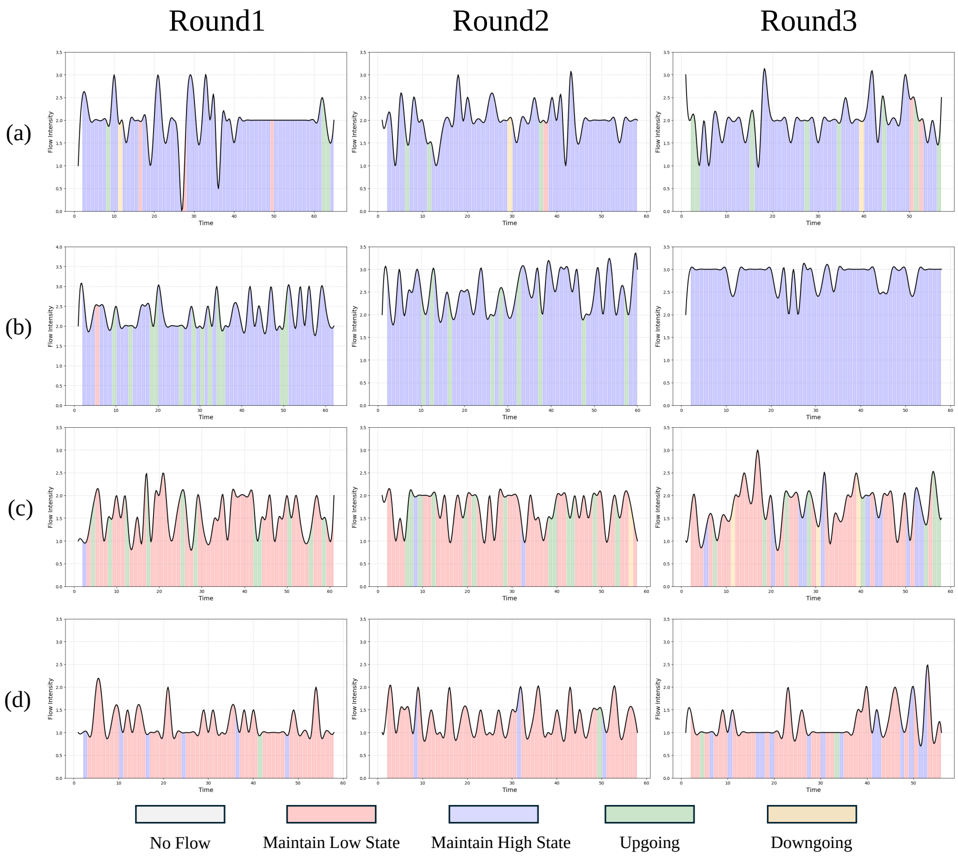


Figure 6: Visualization of flow intensity and flow state: The vertical axis represents flow intensity, the horizontal axis is in five seconds, and the color of the filling bar represents different flow states. Each row represents the model's prediction of the three rounds of game flow status and intensity for different participants.

changes between the two. Additionally, when examining the progression across game rounds (1st, 2nd, and 3rd), distinct patterns emerge. For some participants, achieving high flow becomes increasingly difficult in subsequent rounds, while others maintain similar flow patterns despite varying difficulties. This suggests that individual differences influence how flow dynamics evolve across game rounds.

6.3.2 Case Study of Inconsistencies Between Flow State and Intensity. In analyzing flow state and intensity, we observed that intensity is focused solely on momentary concentration levels, which does not fully capture the overall flow experience or its long-term effects. To address this limitation, we have integrated flow state analysis into our visualization framework, as illustrated in Fig.7. This integration allows for a more comprehensive understanding of the flow experience, its long-term benefits, and individual differences, thereby facilitating a deeper exploration of the flow phenomenon.

- Case (a): As shown in Fig.7(a), although the flow intensity (i.e., the overall height and frequent fluctuations of the curve) appears similar between the left and right graphs, there are significant differences in the flow states. A more granular analysis reveals that the left figure exhibits more pronounced intensity fluctuations and a higher number of non-flow states. In contrast, the right figure also shows considerable fluctuations but with lower frequency, and there are notable low-flow or non-flow states around positions 4, 24, and 48. These interruptions in the flow state may contribute to the perceived lower overall intensity.
- Case (b): As shown in Fig.7(b), both graphs exhibit minimal fluctuations, the primary distinction being flow intensity. From a state perspective, whether at persistently high or persistently low levels, the flow state remains relatively stable with few transitions. This observation may be attributed to the minimal variation in flow intensity or may indicate the stability of the flow state across different intensity levels.
- Case (c): As illustrated in Fig.7(c), there is a further reduction in fluctuations, leading to a smoother profile. The flow states in both graphs predominantly exhibit an upward or downward trend, without transitioning into sustained high- or low-flow states. This pattern may be due to the reduced variation in flow intensity, or it might indicate that the flow

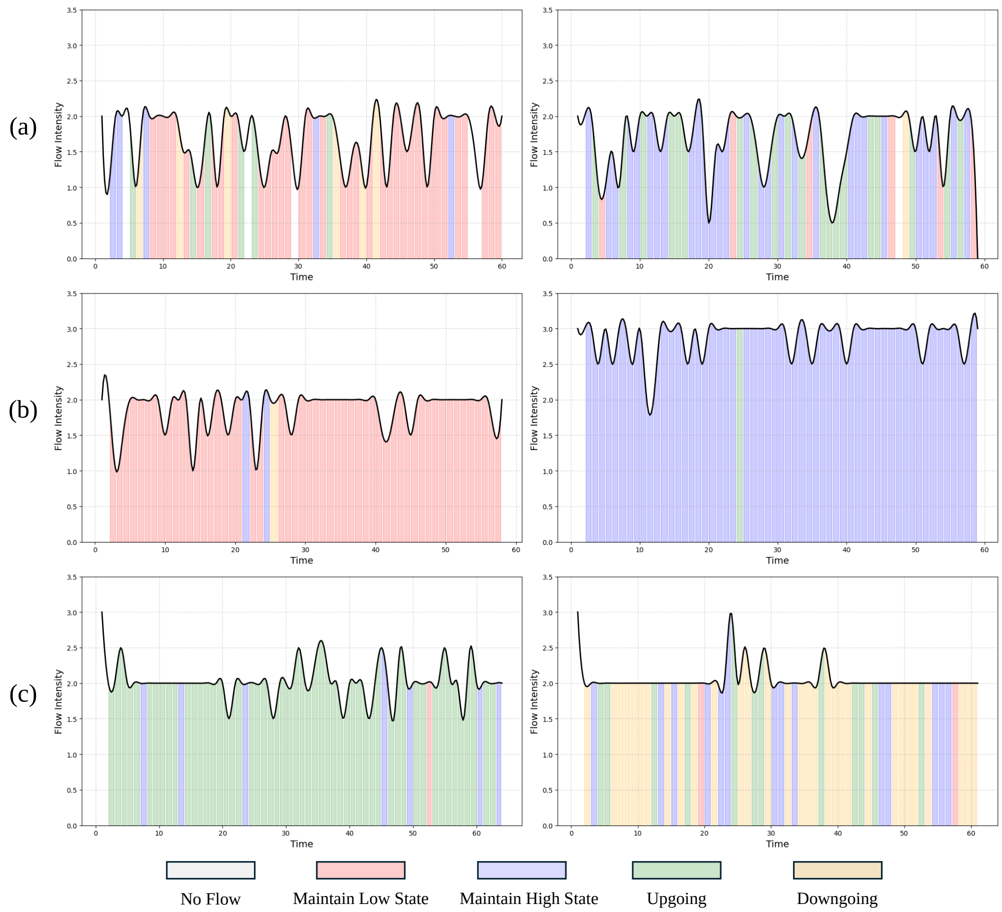


Figure 7: The diversity of flow experiences is illustrated through three distinct flow patterns, each demonstrating unique characteristics in flow intensity and fluctuation.

states are predominantly trending in a single direction rather than oscillating between high and low levels.

6.3.3 Case Study of Individual Flow Changes in Flow Intensity and Flow State. Considering the impact of individual personality differences on flow experiences, this section will analyze the personalized characteristics of flow intensity and flow state at the individual level. It will also explore the implications of these characteristics for participant experience design. As shown in Fig.8, we selected the predicted flow states and flow intensities for two participants over three rounds of gameplay.

In Fig.8(a), it can be observed that the participants primarily experienced an upward flow state during the first round of the game, with significant fluctuations in flow intensity. In the second round, although the flow intensity continued to fluctuate frequently, it remained mostly at higher values, indicating a transition from an upward flow state to a high-flow state. In the third round, the flow intensity was predominantly in the high range, and nearly all participants experienced a high-flow state. These results suggest that the task design and difficulty level were appropriate for the participants.

Unlike the previously discussed participants, the subjects in Fig.8(b) exhibited low levels of flow intensity across all three rounds. In particular, the changes in flow intensity during the first and third rounds showed a completely opposite trend compared to the earlier participants: the flow intensity was relatively high in the first round, while it was comparatively low in the third round. From the process view of flow states, events reflecting high flow levels were more frequent in the first round, but a marked decline began in the second round, with flow states nearly continuously decreasing in the third round. This suggests that the participants had a low level of interest at the beginning of the experimental task, and their interest waned as the task progressed. This phenomenon may be attributed either to the task's low difficulty or to a mismatch between the task format and the participants' interests.

In analyzing the aforementioned case, we found that relying solely on strength levels is inadequate to fully capture the flow experience. Significant inconsistencies between flow states and their corresponding strengths across different visualizations reveal the complexity of flow experiences. To gain a comprehensive

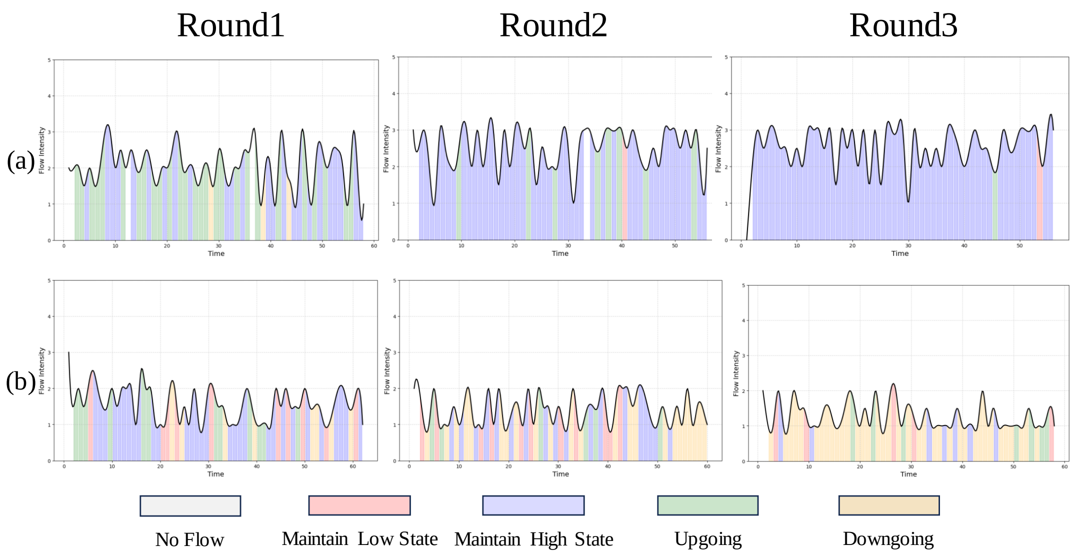


Figure 8: The variation in flow intensity and flow states across rounds among different individuals clearly reflects the differences in psychological experiences in specific task contexts. By comparing the flow performances of various participants, key factors influencing flow intensity can be identified, such as interest, skill matching, and environmental conditions.

understanding of participants' flow states, it is essential to investigate these inconsistencies, including analyzing multiple dimensions such as individual differences, to achieve a more accurate understanding of the flow experience. Building upon this, we conducted a further personalized analysis to explore deeper influencing factors through a detailed examination of individual participants, such as task difficulty and format. Therefore, further understanding of flow can be achieved through visualization technologies. By real-time monitoring and dynamic visualization of the participant's EEG signals, researchers can clearly present the various stages of flow. This visualization not only allows researchers to observe and analyze participants' flow experiences during interactions more intuitively, but also supports enhancing participant immersion and engagement in activities more effectively. The findings provide new insights for the development of human-computer interaction experiences, suggesting the design of adaptive difficulty and format tailored to individual characteristics to help participants maintain high-flow states, thus enhancing the participant experience.

7 DISCUSSION

This paper explored a method to compute and visualize dynamic flow state during the HCI activities based on multi-channel EEG signals from a process-oriented perspective. Several important points are discussed below.

7.1 Granular Measurement of Flow

The introduction of the concept of flow states aids in the measurement and identification of flow. Compared to descriptive methods of the presence or absence of flow, or high, medium, and low intensity of flow, we adopt a more granular approach with four levels of flow intensity. While this provides a more detailed analysis, it also increases the difficulty of characterizing each level due to individual differences. To address this, we have designed descriptions for five flow states. On the one hand, states of continuous high-flow and upward trajectories are generally easier for participants to discern. The low-flow state, on the other hand, is defined as when participants have a certain level of immersion in the current task.

As far as we know, This work is the first attempt to dynamically describe and calculate flow experience from the process view of dynamic processes. We provide a research paradigm to achieve this goal, including constructing flow induction tasks, defining flow experience labels and sampling, constructing a multi-channel EEG signal dataset, proposing targeted flow calculation models and validating them, and visualizing the dynamic process of flow. When predicting flow, we propose to focus on several dynamic states of flow beyond just its intensity. The experiments conducted in Section 6 reveal that such an approach benefits both the identification of flow states and the measurement of flow intensity, furthering our understanding of flow. According to the final results, we have achieved a more advanced method for detecting and visualizing the dynamic characteristics of flow experience from EEG signals than in previous studies [7, 12, 31], which has contributed to some extent to research in this area.

7.2 Multidimensional Analysis of Flow Dynamics

The combination of frequency domain and time domain information facilitates more accurate identification of flow states. Flow experience is a dynamic process characterized by complex variations in electroencephalogram (EEG) signals across different stages. Frequency domain analysis reveals the power distribution and frequency characteristics of EEG signals associated with specific cognitive states, while time domain analysis provides insights into the dynamic changes and real-time features of these signals. By integrating both types of information, we can more accurately capture the complexity and dynamics of flow states, thus enhancing the accuracy and reliability of identification. Our experimental results support the effectiveness of this multidimensional approach, demonstrating significant performance improvements in recognizing flow states and their intensity using the FA-ConFormer model. Future research could further explore the EEG features of flow states and leverage this information to design interventions that promote flow experience, ultimately improving individual performance and satisfaction across various tasks.

7.3 Introduction of the Dynamic Flow Dataset and FA-ConFormer Model

The introduction of the Dynamic Flow Dataset and the FA-ConFormer model represents a significant advance in the field of flow experience computing. These tools facilitate the real-time monitoring and analysis of participants' flow states during their interactions with technology. Notably, the design of the FA-ConFormer framework shares a profound intrinsic connection with flow theory. The global attention mechanism of the Transformer within the model, which integrates global information across channels and time, echoes the top-down control functions of the prefrontal cortex in flow theory. As the brain's high-level cognitive regulatory center, the prefrontal cortex is responsible for maintaining global focus and coordinating activities across various brain regions during the flow state, ensuring the individual's overall grasp of the task. In contrast, the hierarchical feature extraction and local dynamic modeling of deep convolution simulate the automated and efficient information processing process in the flow state by capturing local frequency-domain features in EEG signals layer by layer (e.g., power changes in specific frequency bands, subtle time-frequency dynamics). As described by flow theory, when an individual enters a flow state, task performance exhibits a fluency characterized by "no need for deliberate effort," which stems from the automation and efficiency of cognitive processing, reducing the cost of conscious control.

By precisely capturing changes in brain activity, the FA-ConFormer model can identify when participants enter a flow state and how the intensity of this state fluctuates over time. This capability for real-time monitoring not only enhances researchers' understanding of the dynamic characteristics of the flow experience but also opens up possibilities for designing interactions that better align with participants' psychological states. Furthermore, the predictive capabilities of the FA-ConFormer model allow HCI systems to proactively adjust task difficulty or provide timely feedback, thereby maintaining or enhancing participant flow experiences. Such predictive analytics create new opportunities in personalized learning, game design, and workplace efficiency, enabling systems to adapt dynamically to participants' real-time states and optimize their overall experiences. With the application of these tools, HCI designers and developers can gain deeper insight into participant needs and reactions in various contexts, ultimately leading to the creation of more intuitive, engaging, and participatory interactive environments. This profound understanding of flow states may pave the way for new interaction design paradigms that prioritize participant experience and cognitive efficiency.

7.4 Inspirations for Optimizing Interaction Design

In the field of interaction design, flow regulation methods are of crucial importance for enhancing the participant experience. In the past, flow regulation mainly relied on the results of the flow state or participant performance to dynamically adjust the difficulty of the next task. For example, in a gaming scenario, the system would only reduce the difficulty of subsequent levels after detecting that players had a poor flow experience when they performed poorly in a certain level. However, this result-based regulation method has obvious lag. Participants might have endured a poor experience for a while before receiving the system's adjustment feedback. In contrast, this study brings new breakthroughs to the optimization of real-time interaction design by integrating the recognition and visualization methods for flow intensity and dynamic states. Through the combination of line graphs and bar charts, these visualization results directly provide researchers with a tool for quantitative analysis of flow dynamics. They help researchers clearly identify the associations between different flow states, task difficulty, and individual skills, further laying a visual foundation for adaptive interface design. Based on the results of Experiment 6.3.1 and Experiment 6.3.3, we defined the "upgoing" and "downgoing" states in the flow framework. These two states have significant predictive value for flow changes.

By continuously monitoring the participant's dynamic flow state, the system can anticipate the trends of flow changes in advance. For instance, when it detects that the participant's flow state is showing a "downgoing" trend, the system can proactively take measures, such as reducing the task difficulty or providing additional support, to help the participant regain a smooth experience before the participant's flow experience actually deteriorates. When the system identifies that the participant is in an "upgoing" flow state, it can appropriately increase the challenge to further stimulate the participant's engagement and enthusiasm and maintain their high-level flow experience.

This proactive intervention strategy based on dynamic flow changes has stronger timeliness and initiative compared to the traditional lag-based regulation method. It can precisely match the participant's state changes at different times and achieve real-time optimization of tasks. This not only significantly improves the participant experience, enhances the participant's sense of immersion and satisfaction, but also provides strong support for designers to create personalized interaction experiences. Designers can leverage this method to explore users' unique needs and preferences and customize personalized interaction solutions. In this way, products will have a greater competitive edge in the highly competitive market, be able to provide users with a higher-quality interaction experience that suits their current state, and effectively enhance user loyalty and the market competitiveness of products.

7.5 Limitations and Future Work

There are still some limitations in this study that need to be addressed in future research.

First, expanding features from EEG signals to better detect dynamic flow experience. There is potential to enhance our EEG-based analysis for a more precise representation of the dynamic aspects of flow experiences. Although the current study has successfully identified EEG patterns associated with flow, there is an opportunity to explore a broader range of EEG features that could offer a more comprehensive understanding of flow variability. The next-step work could benefit from incorporating a wider spectrum of EEG markers, which would enhance the sensitivity and specificity of our model in capturing the subtle temporal dynamics of flow, leading to a more nuanced understanding of the flow experience.

Second, enhancing EEG-based flow computation with integration of game content. The current EEG-based flow computation model is possibly further enhanced by integrating the content of the game itself. The interaction between game mechanics and participant psychology is a critical factor in the flow experience, and the computation model might benefit from a more intimate connection with the game's narrative, challenges, and feedback mechanisms. Future research could explore how the structure and pacing of game content influence EEG patterns associated with flow. By aligning the assessment intervals of flow state and intensity with specific in-game events or milestones, we can create a more responsive and contextually aware system for flow detection.

Third, expanding the sample size of the EEG dataset and broadening categorization. To further enhance our understanding of flow experiences and the performance of dynamic flow assessment, expanding the participant pool is crucial. A more diverse and larger-size dataset will allow for a richer analysis of individual differences like personality traits, which can influence flow states, ultimately providing insights into the factors that promote optimal flow. Future work could incorporate a wider range of flow states to develop a more comprehensive model that better captures the intricacies of flow experience.

Fourth, the single-task paradigm poses challenges for broad generalizability. While the "Whac-A-Mole" task is a well-recognized flow-inducing tool and mirrors the single-task approach dominant in current EEG-based flow studies, relying on one task type constrains the generalizability of results to varied contexts. Moreover, our EEG dataset is the first to support simultaneous recognition of dynamic flow states and intensities, thus limits direct comparability with other flow EEG dataset. Future research should incorporate multiple flow-eliciting tasks, diversify the dataset and enable more robust cross-dataset analyses to improve the generalizability.

8 CONCLUSION

From a process view, we construct the first EEG dataset that includes dynamic changes in flow states and flow intensity, to represent the initiation, development, peak, and dissipation of flow experience. Then we propose Frequency Aware Convolutional Transformer (FA-ConFormer) model for assessing the flow experience, with significant improvements in accuracy for predicting flow states and intensity compared to existing methods. Additionally, we develop a visualization technique using the FA-ConFormer model to delve into how flow states correspond to changes in flow intensity, and how the combined representation of flow state and flow intensity elucidates the flow pattern, thereby enriching our understanding of the flow experience.

In the future, we will consider broadening our data collection scope by integrating interactive content and user personality into the evaluation of dynamic flow experience. This approach will improve our understanding of how users interact with various content, improve the less intrusive flow assessment method, and aid in optimizing HCI design.

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