2025 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct)

EEG-Based Prediction of Perceptual Timing Errors in Virtual Reality

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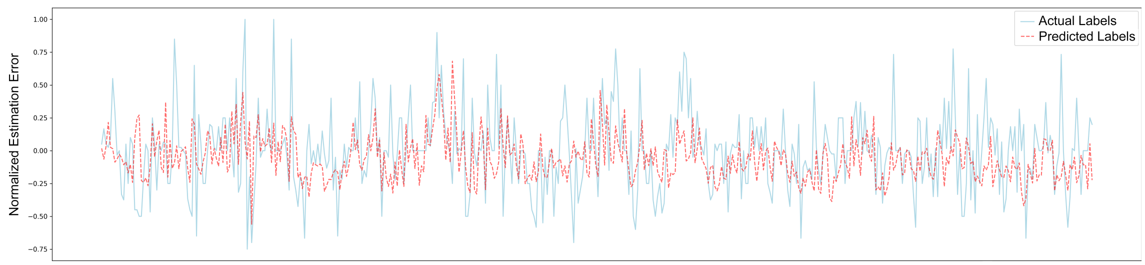

Figure 1: Interval timing error predictions on 270 unseen test samples.

ABSTRACT

Humans do not perceive reality directly, but rather experience a subjective narrative shaped by internal mental states. Research has long sought to understand and measure the accuracy of perception across various sensory modalities and cognitive processes. Recent advances in wearable biosensors and data-driven modeling offer new opportunities to link physiological signals with perceptual distortions. However, most prior work treats perceptual error as a discrete or categorical phenomenon, neglecting its continuous nature. In this study, we investigate whether the *magnitude* of time perception errors can be predicted from brain activity. We trained deep regression networks on $1,386$ EEG samples collected from 33 individuals performing interval timing tasks in virtual reality (VR), labeled with normalized estimation error. Our models achieved a mean absolute error (MAE) of 0.25 and mean square error (MSE) of 0.11 in predicting perceptual error percentage on unseen samples, corresponding to an average error of 14% relative to the central range [–0.75 to 1]. Despite the relatively small dataset, our results demonstrate that EEG signals in VR carry sufficient information to approximate users' perceptual timing errors in real time. This opens a design space for temporally adaptive interfaces that can sense and respond to fine-grained distortions in perceived time.

Index Terms: Time perception, electroencephalography, deep learning, regression, user experience, virtual reality.

1 INTRODUCTION

Human perception offers a subjective interpretation rather than an exact reflection of the external world or objective reality. Instead, it provides an efficient and approximate internal model, shaped by physical, physiological, and psychological states, to support and trigger responses considered optimal from an evolutionary perspective. The representational power of perception, as well as its susceptibility to systematic distortions and illusions, has long been a fascinating topic for academic research. While much of this work has primarily centered on visual perception [15, 44], similar phenomena have been observed across other sensory modalities, such as auditory [49] and tactile perception [26].

Our perception of time is similarly subjective, yet research on temporal perceptual errors remains relatively limited. Factors such as age, personality traits, neural state, mood, cognitive engagement, and the nature of an event can all influence how fast or slow time seems to pass [2, 6, 10, 13, 46, 50]. For example, emotionally charged episodes or simply observing something out of context are perceived as lasting longer than their actual duration [45, 52]. Conversely, we might perceive time as passing faster when an object is moving toward us or during immersive activities like playing video games in virtual reality (VR) [38, 40]. This perceived pace and subjective experience of time is integral to how we make sense of and interact with the world [31].

The discrepancy between objective reality and our subjective perception presents both risks and opportunities. For example, the *size-speed* illusion has been implicated in rail accidents at level crossings [11], while an entire multi-billion-dollar industry was built upon the illusion of motion [1]. Another prominent example is VR as an emerging technology that systematically exploits perceptual gaps to enhance immersion and interactivity. From foundational elements like locomotion techniques and body ownership [12, 18] to modalities like temperature, taste, and smell [8, 9], the effectiveness of virtual environments lies in creating increasingly persuasive perceptual illusions. Therefore, actively monitoring user perception helps to fine-tune perceptual modulation through an online control loop. Such monitoring is not only feasible but increasingly essential, given recent advances in extended reality (XR), artificial intelligence (AI), wearable biosensing, and the growing computational capabilities enabling data-driven modeling.

These developments have paved the way for a paradigm shift in the design of smart and adaptive user interfaces (UIs), with the possibility of sensing and responding to users' momentary perceptual and psychological states. Although still relatively underexplored, time perception offers a rich lens into attention, emotion, cognition, and decision-making. Especially with regard to UI design, monitoring time perception in contexts such as waiting time, decision-making interval, and system response can preempt interaction issues by detecting perceptual deviations from the actual pace of events [19, 28, 43, 48]. Furthermore, aligning system behavior with users' subjective sense of time or improving temporal coordination in remote collaboration settings can enhance user experience (UX), promote smoother human-computer interaction (HCI), and support focus and productivity [7]. However, an objective and

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2771-1110/25/$31.00 ©2025 IEEE
DOI 10.1109/ISMAR-Adjunct68609.2025.00037

real-time measure of time perception remains the missing link in realizing such intelligent and personalized UIs, with this work aiming to address that gap.

2 Related Work

In general, perception is a challenge to measure. When it comes to time perception, this challenge increases in complexity because of uncertainty about the mechanisms responsible for temporal processing.

Time perception is traditionally measured using timing tasks, typically designed in four formats: *production*, *reproduction*, *verbal estimation*, and *discrimination*. In production tasks, participants produce a specified duration through a motor response (e.g., pressing a button for *n* seconds). In reproduction tasks, they first experience an interval and then reproduce the duration with a motor response (e.g., pressing a button for as long as an *X* was displayed on the screen). Verbal estimation tasks similarly expose participants to an interval first, but the duration judgment is quantitative (e.g., reporting the duration in seconds). In discrimination tasks, participants are presented with two intervals and asked to judge which one was longer in duration [5, 30, 36, 51]. However, these approaches rely on self-reporting, which is inherently subjective and prone to misunderstanding, memory lapses, and both personal and central tendency biases [3, 24, 30, 42].

In the last two decades, researchers have turned to various neuroimaging techniques, such as positron emission tomography (PET), electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), and functional near-infrared spectroscopy (fNIRS), to better understand the neural mechanisms underlying time perception [23, 32, 35, 47]. This transition has fueled more ambitious efforts to develop accurate and objective measures of time perception. In this regard, the high temporal resolution and affordability of EEG made it a prominent candidate among other neuroimaging techniques. Consequently, a growing number of studies in recent years have used EEG as an objective metric to evaluate time perception [14, 16, 20, 21, 25, 33, 34, 37, 39]. These studies recorded and analyzed EEG signals using various methods, such as power spectral analysis, the extraction of event-related potentials (ERPs), and time-frequency analysis to identify neural correlates of specific states of time perception, including overestimation, accurate estimation, and underestimation of durations. While these methods offer a high degree of objectivity, their analyses are inherently offline, rendering the results unsuitable for use in real-time feedback loops, such as those in personalized, adaptive virtual environments.

In recent years, a small but growing number of studies have begun to explore online analyses of time perception, using machine learning (ML) techniques and neural networks for real-time classification and prediction of perceptual deviations in timing. Orlandic et al. trained an eXtreme Gradient Boosting (XGB) model on biosignals collected from 18 participants using wearable sensors, achieving a weighted $F1$ score of 77.1% in classifying subjective passage of time into fast and slow categories [41]. Taking a different approach, Fountas et al. adapted a pre-trained convolutional neural network (CNN) to predict the estimated duration of short videos based on the video content, participants' attention levels, and the type of timing task [17]. Hallez et al., following a similar approach, developed a recurrent neural network model called *Cognitive and Plastic RNN-Clock* to simulate the human timing mechanism, based on four features: cognitive plasticity, attention to the passage of time, memory, and the ability to learn duration estimation [22]. In an ambitious effort, Aust et al. tested 11 machine learning algorithms on physiological data alone for the binary classification of subjective time perception. They achieved an accuracy of 79% using a support vector classifier [4].

These studies provide a valuable roadmap for assessing perceptual timing errors within an online feedback loop. However, their methodologies either depend on pre-existing information about users or the detailed content of the experienced environment, or are based on mapping responses onto binary (e.g., correct/incorrect, overestimation/underestimation) or limited categorical classes (e.g., fast/slow, short/long). While the former approach is unsuitable for real-time feedback in generalizable adaptive environments, the latter one reduces the continuity of perceptual experience to a few predefined labels. To the best of our knowledge, this study is the first to explore a generalized, cross-individual mapping of biosignals for capturing continuous errors in time perception.

3 Methodology

In this work, we leverage an existing EEG dataset to investigate whether errors in subjective time perception can be quantitatively predicted from brain activity. We frame perceptual error as a supervised learning problem, modeling the relationship between neural signals and deviations in perceived duration as a regression task. This framing is grounded in the assumption that EEG signals encode cognitive and perceptual states relevant to time perception. Previous work has established a strong and reliable correlation between EEG patterns and temporal processing [14, 16, 20, 21, 27, 29, 37], but few studies have explored whether these signals can support direct, continuous prediction of subjective temporal error. However, our design raises beyond traditionally aggregated and categorical analyses and enables trial-by-trial modeling of perceptual error in timing. By modeling this relationship, we aim to detect and extract hidden markers of perceptual distortion in real time. A successful predictive model would serve as proof of concept that biosignals, such as EEG signals, can reveal internal perceptual states with sufficient resolution to support closed-loop systems. This opens the door to adaptive user interfaces that respond not only to observable behavior, but also to the underlying perceptual states, which are particularly useful in XR, attention-sensitive environments, or systems involving time-critical decisions.

3.1 Dataset

The dataset used in this work was developed in the context of earlier research [39] investigating EEG signatures associated with three time perception states: overestimation, underestimation, and correct estimation. We recruited 33 participants, each of whom completed 42 randomized interval-timing trials, estimating the duration of 2-, 4-, and 6-second trials while exposed to various time perception modulators (See Fig. 2).

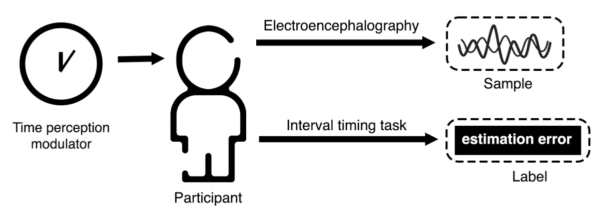

Figure 2: A schematic overview of the dataset creation process.

EEG signals were recorded during the trials from Fz, C3, Cz, C4, Pz, PO7, Oz, and PO8 channels, based on the standard 10–20 EEG system, using an 8-electrode Unicorn Hybrid Black headset[1] (Fig. 3). A total of 1,386 EEG samples were recorded with a sampling rate of 250 Hz, with high- and low-pass cutoff frequencies

[1]https://www.unicorn-bi.com

set at 0.05 and 80 Hz, respectively. Collected samples were preprocessed to remove artifacts (e.g., head movement, blinks) with Independent Component Analysis (ICA) [39].

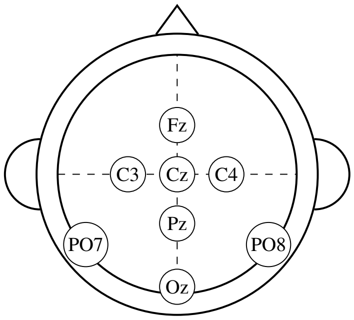

Figure 3: Locations of the EEG device's electrodes on the head.

We used 12 columns from the original dataset, including eight EEG channels recorded as time series, type of time perception modulator presented during trial, trial duration, participant-trial identifier, and participant error in estimating duration. Error in estimating duration was calculated by subtracting the objective duration from the estimated duration and normalized by the objective duration, such that negative values indicate underestimation, positive values indicate overestimation, and zero indicates accurate estimation. The data samples had the shape $(t,12)$, where t is the number of data points in the EEG time series. The constant features were broadcast across all time points to fill their respective columns.

3.2 Preprocessing

Shape Standardization EEG signals were recorded for durations of 2, 4, and 6 seconds, resulting in 1,386 samples of varying lengths. We restructured the original dataset using three approaches. First, we extracted the final 499 rows from each sample, corresponding to approximately 2 seconds of the original recordings based on the EEG device's sampling rate. We used 499 rows, instead of 500, to preserve more samples, as many recordings contained fewer than 500 time points. Six samples contained fewer than 499 time points and were therefore excluded, resulting in 1,380 2-second samples, each with shape $(499,12)$. Second, to increase the number of samples and exhaust the entire recordings, we extracted the remaining rows from 4- and 6-second samples, splitting them into 2, and 3 samples, respectively. This restructured the data to 2,763 2-second samples with the same shape as the first approach. Finally, repeating this procedure with 249 rows, corresponding to nearly 1 second, we created a third dataset of 5,542 1-second samples, each with shape $(249,12)$.

EEG Signal Analysis EEG signals were processed with three analyses. First, we performed *Fast Fourier Transform* (FFT) on each EEG channel to compute spectral power across five standard frequency bands: *delta*, *theta*, *alpha*, *beta*, and *gamma*. This produced 40 new features—5 bands per channel across 8 channels—and compressed each time series into a single row with shape $(1,44)$. Next, we computed *wavelet entropy* for each EEG channel time series to quantify signal complexity and dynamics. This analysis also collapsed time series and added entropy values to the dataset, reshaping each sample to $(1,12)$. Finally, we applied *Hilbert* analysis to each EEG channel to extract four key time series: *envelope* reflecting amplitude modulation; *instantaneous phase*, capturing the signal's position within its oscillatory cycle; *instantaneous frequency*, measuring moment-to-moment changes in oscillation rate, and *fine temporal structure*, representing subtle amplitude-normalized fluctuations. These added a further 32 features to the dataset, with a sample shape of $(t,36)$.

We also processed the categorical feature representing the time perception modulator into a quantitative variable, *Modality*. In the original experiment, participants were exposed to five types of stimuli alongside a control condition. Based on their content, we grouped the stimuli into four categories: animated, visual, auditory, and blank (*i.e.*, control), and encoded the feature into a quantitative variable, accordingly.

Dataset Partitioning We split the dataset into training and test sets with an 80–20% ratio and used cross-validation to allocate 20% of the training set for validation. However, to obtain a balanced test set without data leakage, three criteria had to be met. The original dataset is highly imbalanced, with about 57% of the samples belonging to the underestimation time perception state (*i.e.*, negative labels). Therefore, first, we needed to ensure that the test set contains nearly equal numbers of negative, positive, and zero labels. Furthermore, we aimed to balance the test set with respect to duration variation. Therefore, as longer samples were split into smaller ones, we observed a 1:2:3 ratio for 6-, 4-, and 2-second samples, respectively, within each of the three label groups. Furthermore, to prevent data leakage, it was critical to assign all split segments from a single original sample to either the train or test set. Ultimately, we randomly selected 45 2-second, 30 4-second, and 15 6-second samples from each label group, resulting in 270 samples for the test set. We used the same samples for the test set across all dataset variations.

Feature Normalization We first normalized the training sets by applying robust scaling to the EEG signals and min-max scaling to the modality and trial duration features. The scaling parameters computed from the training sets were then used to normalize the test sets.

3.3 Models and Training

In order to evaluate the complexity of the patterns within the datasets, we implemented three neural network architectures: a feedforward network, a CNN, and a long short-term memory (LSTM) network. At this stage, the dataset size was insufficient for using more complex architectures, such as the Transformer.

Feedforward This is a fully connected network for regression, with seven hidden layers (128–1024 neurons with ReLU activations) arranged symmetrically.

CNN A convolutional network for regression with three Conv1D layers (128, 512, 1024 filters; kernel size of 3; and ReLU activations), each followed by batch normalization and dropout (0.3 and 0.5). This is followed by a global average pooling layer that connects to dense layers (512, 256, and 64 neurons).

LSTM This is a recurrent regression network with three LSTM layers (128, 512, and 1024 units), each followed by batch normalization and dropout (0.3 and 0.5), connected to dense layers (512, 256, and 64 neurons).

Training Each of the 27 configurations (3 sample sizes $\times$ 3 signal analyses $\times$ 3 network architectures) was trained over three independent runs using the Adam optimizer (learning rate 10^{-4}) to minimize mean squared error (MSE), while mean absolute error (MAE) was computed as an evaluation metric.

4 Results

Across all configurations, the mean MAE on the unseen test set was 0.25 ($\pm$0.008), which corresponds to approximately %14 of the label range (see Tab. 1). However, the CNN architecture that was trained using the Hilbert analysis with $2,763$ samples demonstrated the best performance (see Fig. 4 and Tab. 2).

Table 1: Average performance of 27 configurations.

	Test		Train	
	MAE	MSE	MAE	MSE
mean	0.25	0.11	0.22	0.42
std	0.01	0.01	0.02	1.23
min	0.23	0.10	0.18	0.06
max	0.27	0.15	0.27	5.31

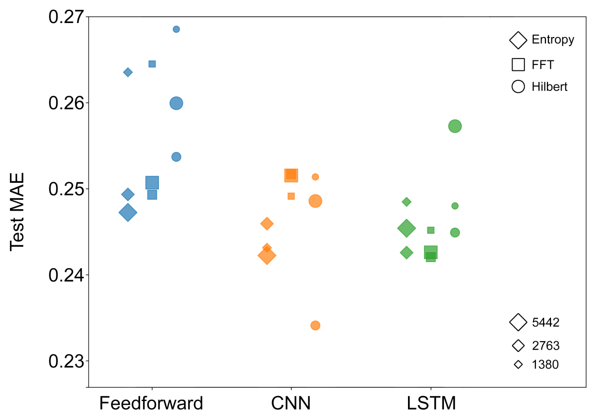

Figure 4: Test MAE across architectures and analyses.

Table 2: Best performances based on test MAE.

	Best Architecture	**Best Sample Size**
Entropy	CNN	5542
FFT	LSTM	2763
Hilbert	CNN	2763

5 Discussion

Our results demonstrate the feasibility of trial-by-trial modeling of perceptual timing errors. As shown in Fig. 1, the model closely follows the general trends in the data. This is particularly notable considering the noisy nature of EEG signals. On average, the model predicted subjective timing errors with a 14% deviation relative to the normalized label range. This corresponds to approximately 0.3 seconds for 2-second and 0.8 seconds for 6-second trials.

Our best result was achieved by the CNN trained on Hilbert time series with 40 features; however, on average, wavelet entropy with the fewest features outperformed the other analyses. This likely reflects the small dataset size, which favors simple representations rather than the analyses' true predictive power. Together with the similar performance of CNN and LSTM architectures, this finding indicates that the temporal dynamics of EEG signals are not essential to predict subjective time perception. Regarding sample size, including the full recorded signals (2,763 2-second samples) improved performance. However, reducing the segment length to 1 second, to increase the dataset size to 5,442 1-second samples, led to weaker results. This suggests that 1-second segments may be insufficient to capture meaningful information about time perception. Nonetheless, the variation in test MAE values was small, and these trends are inconclusive.

Although our models did not outperform those of Fountas et al. [17] and Hallez et al. [22] in predicting fine-grained perceptual errors in duration estimation, they offer a generalizable, online framework that is trained only on EEG signals, without requiring insight into individuals' cognitive capabilities or details about the content of their experience. Such an online, generalizable method represents the most direct advance to date toward real-time perceptual feedback loops in virtual environments.

5.1 Limitations and Future Work

As illustrated in Fig. 1, the model does not fully capture the variance of the dataset, tending to generate a conservative and smoothed prediction curve. This pattern suggests underfitting, which may result from insufficient model complexity. In this study, we avoided using more complex architectures due to the small size of the dataset. Future work will use generative and autoencoder models to create synthesized samples and augment the dataset. Additionally, incorporating other physiological signals could improve training feature stability by balancing potential EEG signal noise. This may also help capture other dynamics and improve the network's ability to accurately model time perception.

6 Conclusion

In UX research, perceptual modalities are often approached as classification problems or addressed with offline analyses that need high levels of personalization. We argue that biosignals, and particularly electroencephalography, are a rich source of information about perceptual states, enabling the development of generalized models that can continuously track perception and its small deviations from reality. The prototype predictive models discussed in this paper resulting from EEG-based deep regression on perceptual timing data in VR demonstrate the practicality and potential of real-time cognitive state inference for designing temporally aware HCI approaches. The successful implementation of such models will bring us closer to achieving truly adaptive virtual environments and intelligent user interfaces.

Acknowledgments

This study has been supported by the European Union's Horizon 2020 research and innovation programme under grant numbers 964464 (ChronoPilot) and CHIST-ERA-20-BCI-001 (BANANA), as well as the European Innovation Council under grant number 101071147 (SYMBIOTIK).

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