Third Time's the Fatigue: Frequency Verification and Its Extended Discussion of Landscape Fatigue Based on Electroencephalogram Measurement

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Abstract: In the context of urban landscape renewal and sustainable development, the use of EEG technology to measure and assess landscape fatigue and its frequency has become a preliminary issue in landscape perception research and practice, aiming to elucidate the characterization patterns and underlying logic of landscape fatigue. This study establishes an analysis framework for landscape fatigue and scenes EEG, builds a brain fatigue measurement model, and conducts an EEG experiment for the frequency statistics, analysis, and discussion of landscape fatigue. First, taking Xiangyang City Wall Park as a case, four elements were selected to organize single and composite scenes, and five experience rounds of EEG experiments were set up to collect the corresponding EEG and transform it into scene brain fatigue data. Moreover, ANOVA, correlation analysis, etc. are combined and used to build a brain fatigue measurement model to quantitatively describe the tendency, amplitude, consistency, and significance indices of landscape fatigue. Lastly, the fatigue characteristic index is used to calculate the interaction effects of multi-element scenes to verify and deduce the frequency rules of landscape fatigue. According to the research results, the brain fatigue value increases gradually with the rise in the landscape experience frequency. Brain fatigue has positive correlations with the landscape experience frequency and becomes stable after the third round of landscape experience. Additionally, the number of scene element types and the cumulative brain fatigue of repeated experience showed an inverted U-shaped relationship, and the collaborative design between elements can effectively alleviate the effect of landscape fatigue. These results verify the existence of "Third Time's the Fatigue" in landscape experience, and relevant rules and conclusions can increase the depth of landscape fatigue research and provide EEG theoretical foundation, experimental optimization paths, and profound professional knowledge for evidence-based research on routine experiential landscape.

Keywords: Landscape fatigue, scene EEG experiment, brain fatigue measurement model, fatigue characteristic index, landscape element

1 Introduction

As global urbanization continuously increases, residents' diversified demands for a good life and landscape experience have become increasingly intense (ZHANG 2023). Although the contemporary urban landscape has been confirmed to aggravate fatigue perception due to high-density visual stimulation and information overload (ZHAO et al. 2024), systematic research on the landscape fatigue mechanism in repetitive visits to routine experiential landscapes is still lacking. It is worth noting that even in scenes dominated by natural elements, single or redundant landscape combinations may cause fatigue (XU et al. 2023). Scientifically measuring and analyzing landscape fatigue, activating and reshaping the negative landscape and its scene experience, has important research value and practical significance for cultivating a temperature and quality urban landscape.

The concept including "limit to three" has been deeply embedded in human social cognition and practice and existed as rules and idioms in Eastern and Western contexts (JOHNSON et al.

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2015; CONFUCIUS. n.d.). This concept reveals human sensitivity to repetitive issues and may relate to fatigue in landscape experience (LI et al. 2018). Specifically, negative reactions, such as decreased attention, emotional numbness, and even boredom, the pre-neurological status changes of which is known as "brain fatigue", often occur when people visit the same landscape many times. The change patterns of landscape fatigue frequency are characterized and excavated by more refined and standardized measures of brain fatigue and effectively ease and transform landscape fatigue after frequency verification, helping landscape designers create a landscape environment that is more in line with the perceived needs.

1.1 Research Progress on Landscape Fatigue

Landscape fatigue is the perceptual adaptation and neural shielding process that occurs when experiencing the same scene multiple times (ZHAO et al. 2024). The fatigability associated with landscape fatigue is a negative, cumulative physiological or psychological response, which specifically points to individuals' perceptual attitudes toward the landscape and its components.

Landscape fatigue research was initially applied in research on visual aesthetic fatigue and fatigue behavioral risk assessment (HU et al. 2023). More recently, studies and practices have focused on the human-scale characteristics of the landscape and its social and economic benefits (BISHOP 2019). This shift has expanded research into fields such as physical environments, perceptual recovery, visual quality, and landscape preferences (MACAULAY et al. 2022, MEDEIROS et al. 2023). However, the existing studies mainly investigate short-term fatigue recovery but rarely discuss the mechanisms of synergy between landscape composition and fatigue frequency. Field evaluation and paper questionnaire methods are applied in existing studies. In the process of data acquisition, there are some shortcomings such as strong subjectivity and limited real-time.

1.2 Application of EEG Technology in Landscape Fatigue

Brain fatigue, a quantitative feedback of landscape fatigue, and one of the key measures of landscape influence, refers to a state of instantaneous nervous exhaustion arising from repetitive stimuli to people (AHN et al. 2016). An Electroencephalogram (EEG) is a non-invasive bioelectrical signal of brain activity (KIM et al. 2020), able to capture rich brain changes in real time and provide high temporal resolution data, whose α, β, θ, and δ rhythmic waves, along with their ratios, have been proofed to be effective indicators of brain fatigue in landscape environments (XIAO et al. 2024).

At present, the study of landscape brain fatigue combined with EEG technology has made preliminary progress in the fields of virtual experience and scene design. (BOFFI et al. 2022). However, it is still difficult to effectively solve the problem of factors variables that cannot be directly observed in landscape fatigue frequency analysis, and the efficiency of experimental verification and the accuracy of measurement model need to be improved. EEG experiments were carried out according to the changes and distribution characteristics of landscape fatigue frequency, to obtain computable and comparable scene brain fatigue data, construct measurement models and verify the frequency impact of landscape fatigue, thereby expanding the research depth and professional field of EEG analysis of landscape fatigue in landscape environment analysis, evaluation and design.

Against this backdrop, this study is intended to build an analysis framework for landscape fatigue and scene EEG to reveal the characterization rule and underlying logic of "Third Time's the Fatigue" in landscape experience using EEG. Taking the Xiangyang City Wall Park as a case, organizing combined landscape elemental scenes, conduct scene EEG experiments and brain fatigue data collection to establish the brain fatigue measurement model combined with mathematical statistics, to verify the frequency of landscape fatigue and the interaction effect of factors, and to discuss the practical applications of landscape fatigue research. It provides empirical evidence and practical tools for routine experiential landscape perception and its evidence-based research.

2 Methodology

This study, employing scene EEG data as the primary research object, introduces a quantitative method for assessing landscape fatigue using EEG measurement. This method integrates core algorithms such as brain fatigue transformation technology, ANOVA, and correlation statistics to achieve comprehensive data analysis. It identifies landscape fatigue indices, calculates the interaction effects of scene element combinations, explores landscape fatigue frequency change patterns, and uncovers relationships between factors. The method involves three steps: experimental setup, EEG transformation, and measurement analysis of landscape fatigue (Figure 1).

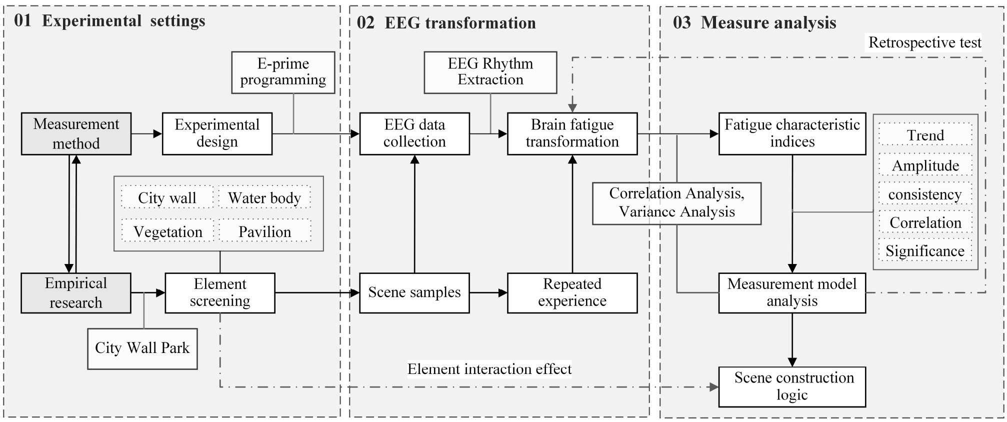

Fig. 1: Technical route

2.1 Settings of Scene EEG Experiment

The complexity and variability of real-world scenes make it challenging to fully control the various factors by landscape fatigue frequency-related experiment (BADLAND et al. 2010). By organizing elements, controlling variables, and other basic settings of laboratory scene images, this study simplifies the relationship between landscapes and fatigue, contributes to accurately capture the corresponding relationship between specific scene elements and brain fatigue indicators. The selection criteria for landscape fatigue-related scene elements should account for perceptual characteristics and the attributes, types, and significance of environmental components (LAN et al. 2023). In this study, the city wall park, a daily destination for residents with a uniform landscape style, was selected as a case study. Four frequently recurring landscape elements – city walls, water bodies, vegetation, and pavilions – were standardized using Adobe Photoshop to create experimental scene image samples (Figure 2).

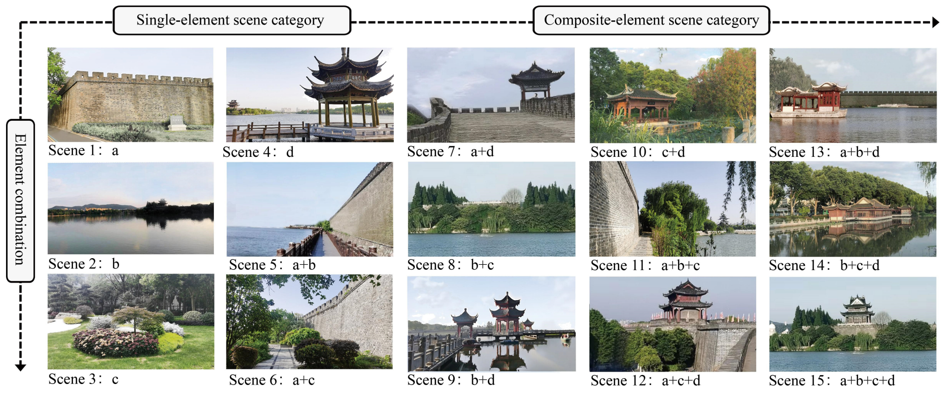

Fig. 2: Examples of scene experimental images

Considering external interference, time and space constraints and other experimental error factors, the EEG experiment was conducted in a confined immersive space equipped with a SAGA 32-bit EEG and TMSI Polybench system, taking advantage of the E-Prime psychology experiment platform to set up the scene image stimulus presentation and EEG data acquisition system. The sample size for the experiment was calculated using G*Power software (size of dz = 0.25; α = 0.05; Power = 0.95; Corr among rep measure = 0.5; Nonsphericity correction = 1) resulting in a required size of ≥ 32 subjects. Considering potential losses and actual statistical power, a total of 42 subjects were recruited (male-to-female ratio 1:1, mean age 30.4 ± 4.5 years). All subjects had similar educational backgrounds and urban living experiences, signed informed consent forms. The experiment was approved by the Ethics Committee and adhered to the ethical standards outlined in the Declaration of Helsinki.

In the experiment, subjects were seated in a fixed position (with a viewing distance of 3.5 meters) facing a 3.2m×8.6m single-curved projection screen (with a 4K resolution). They were required to watch 15 categories of randomly played scene samples, with 5 to 6 images per category, each shown for 3 seconds, over a total of 3 times to reduce the influence of individual differences and random errors on experimental results. Each experimental session lasted approximately 15 minutes including recovery intervals for resting-state EEG (Figure 3). Subjects repeated the experiment at the same time each day for 5 consecutive days, with filling in the fatigue self-rating scale before and after each scene image test (GHARAGOZLOU et al. 2015). Raw EEG signal corresponding to each scene were collected and imported into Matlab_EEGlab for further processing.

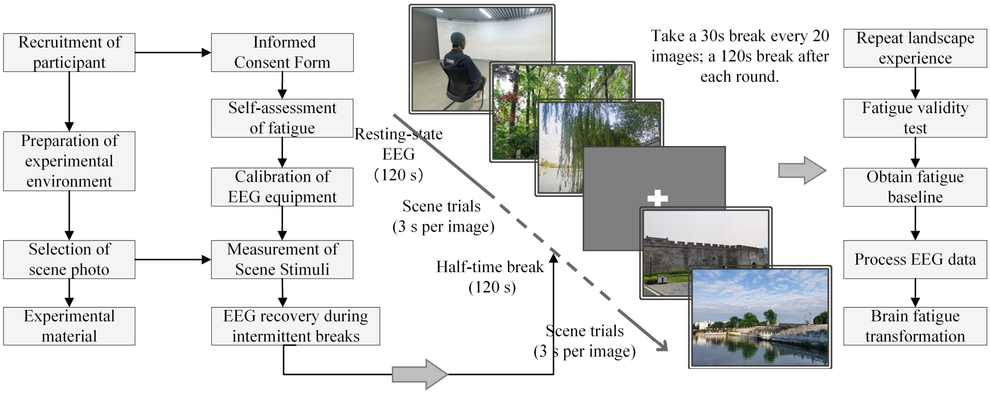

Fig. 3: Landscape fatigue EEG experiment procedure

2.2 Transformation of Brain Fatigue Data

The original EEG signals collected in the experiment contained lots of artifacts and lacked functionality. So, it was essential to transform them into integrated and interpretable brain fatigue data to explore the frequency characteristics of landscape fatigue. The transformation of brain fatigue data involved three parts: scene reclassification, rhythm wave superimposition, and brain fatigue calculation. First, EEG data corresponding to disordered scene images from the indoor experiment were reclassified based on scene categories and pre-processed using baseline correction, artifact removal, and band-pass filtering. Second, the power spectral density (PSD) of the α, β, θ, and δ rhythms from the averaged reclassified EEGs was superimposed. Finally, brain fatigue data were calculated for individual round of landscape experience using rhythm wave ratios. (Eq. (1-2)).

$$F_t = \left(\frac{P_t(\theta)+P_t(\delta)}{P_t(\alpha)+P_t(\beta)} - D_t\right) \times 100\% \tag{1}$$

$$Z_j(i) = z_j(i)/\frac{1}{n}\sum_{j=1}^{n} z_j\,(i) \tag{2}$$

Where, F_t denotes the value of brain fatigue at the $(t)^{\text{th}}$ round of landscape experience, P_α, P_β, P_θ, and P_δ denote PSD of the EEG rhythms α, β, θ, and δ ; D_t represents the fatigue baseline of the $(t)^{\text{th}}$ time (calibrated by both fatigue self-rating score and resting-stage EEG); $Z_j(i)$ is the dimensionless brain fatigue value of the $(j)^{\text{th}}$ subject in the experience of the $(i)^{\text{th}}$ scene; n is the quantity of scenes.

2.3 Analysis of Landscape Fatigue Measurement

To interpret the frequency characteristics of landscape fatigue and obtain more accurate results regarding its effects, it is essential to construct a brain fatigue measurement model by applying appropriate mathematical and statistical methods. Given the high temporal dimensionality of cerebral fatigue data and the complex interplay of environmental factors (TABRIZIAN et al. 2018), this study develops a mathematical-statistical measurement model to extract characteristic indices of landscape fatigue, including trends, amplitudes, consistency, correlations, and significance. offering a scientific basis for validating the rationality of the scene structure and the frequency effects of landscape fatigue.

The measurement model employs the Kolmogorov-Smirnov (K-S) test, paired-sample t-test, and intraclass correlation coefficients (ICC) to validate the distributional assumptions of the brain fatigue data. Spearman's rank correlation analysis is applied to investigate the relationships between brain fatigue metrics, subjective fatigue ratings, and cross-round brain fatigue dynamics. Furthermore, the reliability and validity of the scenario element grouping structure are assessed using Cronbach's alpha coefficient and the Kaiser-Meyer-Olkin (KMO) sampling adequacy test. Subsequently, One-way and multi-way ANOVA were utilized to analyze differences across scene group timings, providing insights into the trends, magnitudes, correlations, and significant feature indices of landscape fatigue frequency changes. To further refine the analysis, deviation contribution function (CAI et al. 2022) was introduced to calculate the interaction effects of landscape fatigue factors， and to explore the underlying causes of the differences (Figure 4).

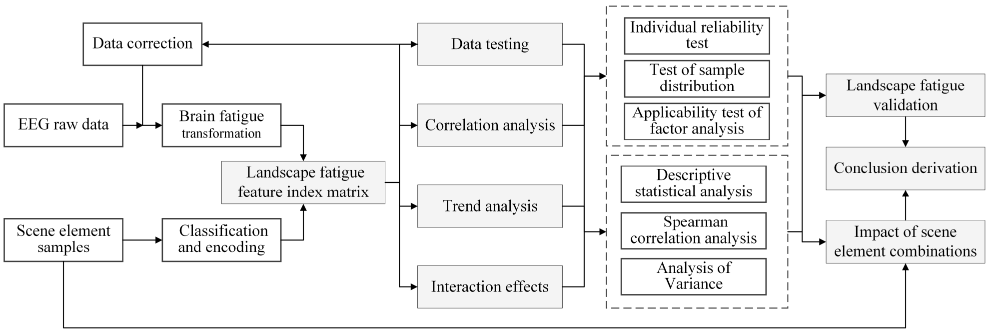

Fig. 4: Landscape fatigue measurement procedure

3 Discussion of the Results

3.1 The Relationship between Repeated Experience Frequency and Brain Fatigue

In this study, a total of 37 subjects were included in the five rounds of repeated landscape experience. There was a slight but significant positive correlation between the brain fatigue index and the self-assessment results (r = 0.44-0.75, p < 0.05), which may arise from the multidimensional nature of brain fatigue (PALMER et al. 2001) and temporal resolution discrepancies contributing to weakened time-series associations. The K-S test confirmed the normal distribution of the brain fatigue data (D = 0.12, p = 0.15), while the ICC test demonstrated high internal consistency of the measurements (Table 1). Significant positive correlations were observed between brain fatigue values across different rounds (p < 0.05), while no significant cumulative fatigue was detected within individual testing rounds, further validating its effectiveness as an indicator for landscape fatigue analysis.

The cross-round time series analysis showed that the brain fatigue in the first three rounds increased significantly (p < 0.01), and the subsequent rounds maintained a high level (Figure 5). Simultaneously, the dispersion of brain fatigue data in the first round was the largest, and tended to be stable after the third round (Table 1). These findings suggest that when evaluating landscape fatigue, we should not only consider the novelty and peculiar feeling of the landscape at the first experience, but also fully consider people's adaptability to landscape changes in combination with the objective data obtained through repeated verification. Although the brain fatigue data from the standardized static-scene experiment (LI et al. 2018) show a trend similar to on-site repeated visitation patterns and have good internal consistency, its ecological validity still needs verification via comparative studies with dynamic real-world scenes. Additionally, individual differences, familiarity, regional conditions as well as social background will affect landscape fatigue perception to some extent (MEDEIROS et al. 2023). Therefore, the analysis of brain fatigue in repeated landscape experience is not only an examination of landscape fatigue, but also reflects the fitting process of continuous adaptation and adjustment between people and landscape.

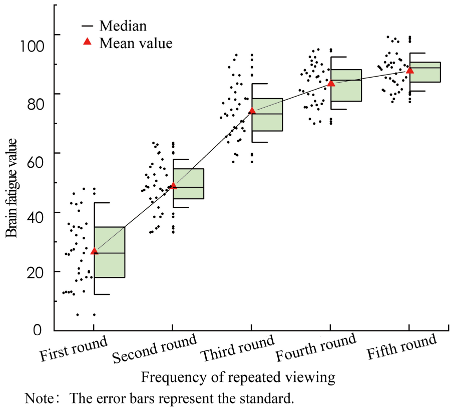

Fig. 5:
Changes in the brain fatigue frequency during 5 rounds of repeated landscape experiences

Table 1: Descriptive statistics of brain fatigue after 5 rounds of repeated experiences

	Sample Size	Mean	Standard Deviation	Standard Error	Coefficient of Variation	ICC
First round	37	24.61	11.70	1.92	47.60%	0.79
Second round	37	51.21	8.64	1.41	16.89%	0.74
Third round	37	72.23	9.52	1.56	13.18%	0.82
Fourth round	37	84.42	6.89	1.13	8.17%	0.82
Fifth round	37	88.58	7.11	1.16	8.03%	0.85

3.2 The Landscape Fatigue Frequency Characteristics of Scene Groups

The brain fatigue data are classified according to scene categories. The Cronbach's α coefficient is 0.806 > 0.8, KMO sampling result is 0.724 > 0.5, and Bartlett's test of sphericity shows a significant probability ($p < 0.01$), supporting the data structure of the scene element combination. There is a significant correlation between 15 scene categories and landscape fatigue ($p < 0.05$), as well as a significant increase of brain fatigue during the first three rounds of repeated experience ($p < 0.05$), with subsequent increases decreasing (Figure 6). Among them, the brain fatigue values of the two and three element combination scenes are generally low in the five rounds of repeated experience, while the increase of brain fatigue in single and four element combination scenes is larger between the second and third rounds, and reaches a higher level after the third round (Figure 7).

Landscape fatigue shows nonlinear evolutionary trajectories, which are regulated by the combined structure of scene elements and the frequency of repeated experiences. In the early stage of repeated experience (round 1-3), brain fatigue accumulated significantly due to the consumption of cognitive resources due to brain adaptation to new and different stimuli; while at the later stage (round 4-5), brain fatigue tended to stabilize due to the activation of the compensatory mechanism of the nervous system, reflecting the regular change of "Third Time's the Fatigue". At the same time, the number of scene element types and brain fatigue showed an inverted U-shaped relativity: moderate element combination scenes (with 2 to 3 types) showed a good effect on regulating brain fatigue, while the monotonous stimulation of single element scenes and the information overload of four element combination scenes will accelerate the accumulation of brain fatigue. In this regard, optimizing the combination of scene elements during the landscape experience process is of great significance for alleviating landscape fatigue. For example, adopt a moderate combination of elements in a node scene, control the length of visual exposure in a single – element area, and set up a spatial buffer in scenes with high complexity to adjust the stimulus intensity of the landscape, which helps to improve the richness and hierarchy of the landscape, optimize the allocation of perceptual resources, and create a sustainable landscape recreation environment for users (GRANH et al. 2010, XU 2024).

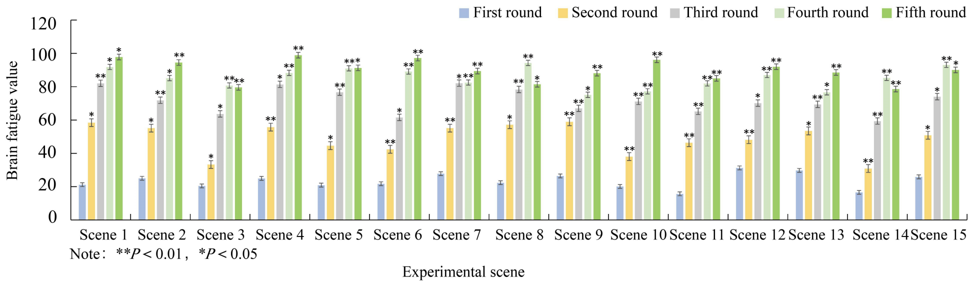

Fig. 6: Comparison of brain fatigue data from repeated experiences in various scenes

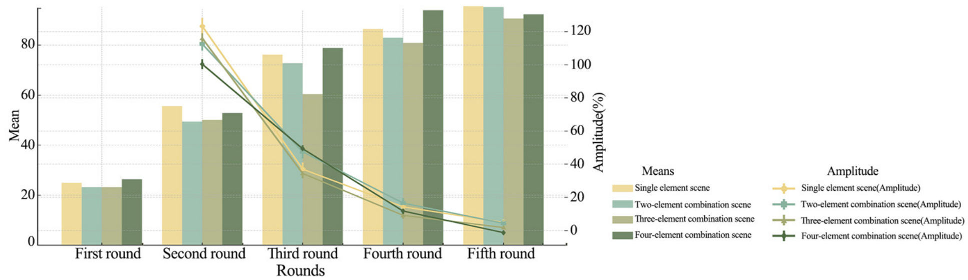

Fig. 7: The variation in landscape fatigue across scene groups

3.3 The Landscape Fatigue Interaction Effect of Element Combination

ANOVA is conducted on brain fatigue data before and after the repeated landscape experiences, showing that the samples meet the homogeneity of variance assumption. It is indicated by contribution rate analysis that the explanatory power of city wall (68.47%), vegetation (13.23%), and water body (10.10%) to landscape fatigue decreases in turn ($p < 0.05$). Scenes dominated by city wall elements (e. g., Scene 6 and Scene 12) show a noticeable increase in brain fatigue after the second round of experience, while vegetation and water body dominated scenes (e. g., Scene 3, Scene 8, and Scene 13) gain a relatively small cumulative rate of brain fatigue. The data show that although the city wall, as a typical artificial structure, has strong visual impact, its single shape and closed space may lead to high fatigue accumulation in repeated experience. In contrast, the natural landscape dominated by water and plants shows better landscape fatigue relief effect, which may be due to the natural characteristics of diverse plant morphological changes and flexible water (GRAHN et al. 2010).

According to the factor combination effect analysis (Table 2), the interaction effect of city wall × water body × vegetation × pavilion is significant, but the amount of effect is low, indicating that hypercomposite scenes may lead to element function antagonism. Among them, city wall × water body ($F = 4.56$, $p = 0.032$, $\eta^2 = 0.12$) and water body × pavilion ($F = 5.23$, $p = 0.024$, $\eta^2 = 0.15$) have a positive synergistic effect, indicating that a reasonable combination can partially offset the negative impact of fatigue accumulation. In conclusion, there is an optimal threshold for the combination of scene elements to alleviate brain fatigue caused by repetitive landscape experience. It also means that in the routine experiential landscape design, taking into account the short-term visual effect and long-term experience quality, paying attention to the quantitative combination design of artificial structures and natural, dynamic and static, open and closed space elements, has the possibility to break through the dilemma of "high frequency – high fatigue".

Table 2: Interaction between landscape fatigue factors

Factor	**Sum of Squares**	**df**	**Variance Homogeneity**	**Sig.**	**Effect Size**	**Contribution Rate**
City wall	99.176	1	71.422	0.017*	0.320	68.74%
Water body	128.724	1	2.228	0.026*	0.027	10.1%
Vegetation	0.695	1	0.583	0.003**	0.046	13.23%
Pavilion	1.337	1	0.000	0.214	0.005	7.93%
City wall × Water body ×Vegetation × Pavilion	257.448	13	93.421	0.031*	0.052	–
Pre-test		1	47.658	0.000 **	–	–
Residual	283.148	8	–	–	–	–

Note: The dependent variable is the fatigue level after the third round of landscape experience (post-test), with the baseline value of brain fatigue (pre-test) as the covariate. The effect size is represented by partial η^2, indicating the proportion of total variance explained by each factor. $^{**}p < 0.01$, $^{*}p < 0.05$

4 Conclusion and Outlook

This study combines scene organization, EEG experiment, measurement model, thereby proposing a method for verifying landscape fatigue frequency based on EEG measurement. Compared with previous research, this paper introduces improvements in three key aspects. First, by conducting the scene EEG experiment to measure brain fatigue in repeated landscape experience, a preliminary attempt was made to change the traditional landscape fatigue subjective evaluation. Second, by establishing a brain fatigue measurement model and extracting landscape fatigue characteristic indices, it becomes feasible to interpret the frequency patterns of landscape fatigue, thus enhancing the operability and verifiability of landscape fatigue research. Finally, by using the landscape fatigue characteristic indices to evaluate the interaction effects of element combinations in scenes, the study can guide the evidence-based design of routine experiential landscapes.

At the same time, the frequency verification method of landscape fatigue based on EEG measurement has practical application potential in perception evaluation, landscape design and participation in governance. In terms of evaluation, by setting three rounds of basic verification cycle, the number and depth of perception evaluation is optimized, which helps to avoid the waste of resources caused by excessive evaluation and improve the efficiency of perception evaluation. In terms of design, on the basis of EEG measurement data, landscape designers are expected to further identify the quantitative design basis of "recreation sequence – key scene – element combination – fatigue threshold" to alleviate landscape fatigue and realize evidence-based landscape renewal. In terms of governance, this method provides the possibility for designers, experimenters, builders and other multi-agent to build a practice field of collaborative participation. Through multiple rounds of data feedback and dynamic adjustment mechanism, it can crack the "decision-demand" structural deviation of the main body participation (ARNSTEIN 1969), and provide a technical fulcrum for the optimization of governance procedures and overall performance.

There are still some limitations in the research. The study focuses on the basic analysis of the characteristics of fatigue frequency in visually static element-composition scenes, and whether the findings can be applied to the study of cumulative fatigue and recovery effects over long time needs further validation. Additionally, the optimal scene combination threshold for alleviating landscape fatigue also requires empirical research for confirmation. Moreover, there remains a gap between indoor scene experience data and real-world environmental brain fatigue data, and the collection and processing of related data remain the fundamental link that constrain landscape fatigue reliability and validity. Future studies should further verify the stability and applicability of landscape fatigue data in evaluating different situational perception models, broaden the scope of landscapes, expand landscape element variables, and refine the differences in experimental subjects. These efforts will collectively drive the detailed and systematic development of landscape fatigue studies.

In human-landscape interactive development, landscape fatigue perception is closely correlated to routine experiential landscape. In the past decade, the application of EEG measurement has provided new exploration perspectives and solutions for the landscape perception evaluation, driving the continuous deepening of verifiable and explainable landscape fatigue frequency research, and further strengthening landscape designers' awareness of rational, evidence-based research-oriented practice. The relevant research shows potential in the fields of landscape behavior psychology, therapeutic landscapes, and even intelligent gardens, but at the same time, the prospects and challenges coexist. Further research should take a more positive attitude towards landscape design and adopt a broader and integrative perspective to study landscape design to make high-quality landscape renewal of the built environment based on an analysis of landscape fatigue figures, thus giving a professional response to the real problems to people's demands.

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