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The Impact of the Audio-Visual Environment in Urban Parks on Mental Fatigue Recovery

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Abstract:

The audio-visual environment in an urban park has a significant impact on participants' recovery from mental fatigue. In this study, an electrocardiogram (ECG) data was combined with the audio-visual environment using a intelligent wearable device. NN.mean and PNN50 were selected as ECG indicators to assess mental fatigue status. For the visual environment, the panoramic view method was chosen, which more accurately reflects the accurate level of visual elements in the human visual. For the auditory environment, LAeq was selected as the indicator. Correlation analysis of these three aspects was carried out, and a regression model of the ECG data was developed. The results of the study showed that Panoramic Green Visibility, Panoramic Sky Visibility, and the ratio of these two was significantly correlated with mental fatigue recovery ($p < 0.01$) and also had a high coefficient of determination over a short period and that changes in LAeq in the park environment were not significantly correlated with participants mental fatigue recovery.

***Keywords**: Mental fatigue recovery, Audio-visual environment, Panoramic view, Regression analysis, Urban parks*

I. INTRODUCTION

Overwork-related diseases have become a significant public health problem in East Asian countries, and the situation is becoming increasingly severe worldwide [1]. Overworked is not simply linearly related to the length of time worked. Therefore, mental fatigue is a better way to detect potential overwork. Mental fatigue is a state of the temporarily reduced maximal cognitive capacity of the brain caused by prolonged cognitive activity, manifested externally by drowsiness, lethargy, or diminished concentration. Medical theoretical studies have shown that overwork had become a significant cause of sudden fatal illness[2], and that high- intensity work increases the probability of cardiovascular disease [3]. In addition to its detrimental effects on physical health, mental fatigue has numerous effects on

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memory, judgment, decision-making ability, and emotional management [4], and prolonged overwork can lead to stress, and strain, and to more serious accident and absenteeism rates and lower productivity [5, 6]. More than a quarter of the world's brain workers are currently at risk of being overworked. Mental fatigue caused by overwork can lead to a range of symptoms such as reduced sleep quality, stress and anxiety, and indirectly to a range of chronic disease risks such as cardiovascular disease [7] and diabetes [8].

Today, theories of recovery of the human mind through the natural environment fall into two main categories. Stress Recovery Theory (SRT) [9] suggests that negative emotions, short-term physiological changes, and behavioral disorders may occur when individuals are exposed to stress, and that in certain environments, such as moderately complex, visually focused, natural environments containing plants and water, individuals' attention is easily drawn to block negative thoughts, suppress negative emotions, stimulate positive emotions, and restore disturbed and dysfunctional physiological functioning to When positive emotions are fully evoked, cognitive and behavioral abilities that were previously depressed are restored. Attention Recovery Theory (ART) [10] suggests that in certain environments, mental content, environmentally encouraged activities, and personal tendencies that are different from the usual context can be elicited. These features can elicit unintentional attention and allow for a good recovery of focused attention. Some natural landscapes can visually stimulate the parasympathetic nervous system and calm the sympathetic nervous system to lower heart rate, and blood pressure [11]. Several previous field studies have explored the visual stimulation effects of different open spaces to compare the psychological recovery effects of diverse open spaces [12-14]. Some studies have used descriptive quantification of visual landscapes (e.g., cultural dimensions, foreground dimensions, etc.) to explore the extent to which visual landscapes in green spaces affect psychological responses [15]. Green spaces can also enhance the quality of the living environment by visually shielding noise sources [16, 17], and this display of visual landscape vegetation produces an additional noise attenuation effect [18].

In recent years, several studies have shown that natural sound environments are more effective than noisy environments for human recovery from stress [19, 20], and others have explored the relationship between different spaces within cities and restorative benefits [21, 22]. According to the World Health Organization on Quality of Life Brief Scale (WHOQOL-BREF), residents of quiet areas have higher average scores on mental health than noisy areas [23].

Neither visual factors nor auditory variables should be overlooked when exploring the impact of the audio-visual environment on human responses, especially in urban parks. It is therefore essential to advance multiparty collaborative quantitative theoretical research to establish urban parks that can more effectively alleviate mental fatigue.

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II. METHODS

2.1 Determination of fatigue stat

Although the study of mental fatigue is essential for the physical and mental health of brain workers, mental fatigue is difficult to measure in real life. Currently, there are four main types of methods for quantifying mental fatigue: subjective scale methods, objective experimental methods, observational methods, and physiological index measures. Personal scales require subjects to assess their level of mental fatigue through questionnaires [24-26]. Although efficient and straightforward, the subjective scale method is relatively inaccurate due to the varying medical levels of the audiences themselves, resulting in relatively low objective accuracy of subjective scales. Objective experimental quantitative methods design some awareness tasks to assess the performance of the test subject's brain functions. Some tasks measure reaction time, memory, and decision-making, such as the Psychomotor Vigilance Task (PVT) [27], the Multiple Sleep Latency Test (MSLT), and the Maintenance of Wakefulness Test (MWT) [28]. The observational method is rarely used to quantify mental fatigue, which is reflected by observing the subject's sleepy state, such as blinking, yawning, and other physiological conditions.

All three of these measures are intrusive in that the user must stop their current work to complete the questionnaire or awareness task. Therefore, these methods cannot be used to monitor mental fatigue in daily life. Physiological indicator measures can be used to detect fatigue in the human body while taking into account daily tasks. Electroencephalography (EEG) is widely used to monitor mental fatigue in drivers [29]. Forty spectral features were extracted from the EEG signal and trained with an SVM model to achieve 86% accuracy in fatigued driving recognition [30]. Although the EEG has been referred to as the 'golden indicator' for monitoring and is widely used for fatigue detection [31-34], the devices used for EEG-based fatigue detection usually have multiple channels and electrodes, which are not suitable for use in daily life. A convenient wearable smart device that can monitor fatigue status at all times [35].

With the latest developments in health information technology and the popularity of smart wearable devices such as smart bracelets, real-time and remote health monitoring, and management have become possible. Many smart sensors for continuous acquisition of physiological parameters have emerged in recent years, such as portable ECG, heart rate and blood pressure sensors with Bluetooth wireless transmission [36, 37]. The wearable ECG device is a real-time mental fatigue monitoring device. It can acquire ECG signals in a more convenient way than EEG devices. Early studies have shown a correlation between the Autonomic Nervous System (ANS) and cardiac rhythm [38]. Therefore, ECG data can be used to measure mental fatigue [39].

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A total of 24 healthy participants without heart disease were recruited. The main reason for this is that mental fatigue is a transient state that varies over time. Participants who feel tired one day may feel energized the next day. Therefore, it is challenging to employ participants who happen to be in a state of fatigue before the experiment begins. In contrast, we chose an alternative method of controlling for the fatigue state of healthy participants by employing a test. Before the investigation, participants were asked to get at least 8 hours of sleep the day before, to refrain from alcohol for 24 hours and caffeine for at least 12 hours before the test to be sure they were in a non-fatigued state [40], and to study and work for 2-4 hours on the day of the survey to reduce errors in mental responses [41].

2.2 Quantifying landscape elements

There are several problems with the previous research of quantifying the visual parameters of Green Vision (%), Sky Visibility, and paving Visibility. The quantification of these landscape elements is usually calculated using a grid approach, whereby areas of vegetation in an image are artificially identified, and their proportion of the grid area is calculated.

As most of the quantitative data is measured based on the extent of the view plane, its proportion does not reflect the actual level of visible greenery in the space surrounding the human eye. At the same time, the angle of the photograph and the focal length of the lens on which the statistics are based are subjective and uncertain, which can impact the assessment results. Based on panoramic images, the concept of Panoramic Green Visibility (PGV) is proposed based on the traditional green vision and defined as the percentage of visual green rate in the spherical field of view of a person standing at a fixed position looking around.

Panoramic Green Visibility uses a panoramic spherical image to replace the two-dimensional image used in traditional green vision. Compared to conventional green vision indicators, There are two advantages to this approach. Firstly, the Panoramic Green Visibility reflects the 360°green view of the designated site, which is consistent with the subjective visual perception of people and reliably reflects the visible green rate of the surrounding environment of the site. Secondly, the panorama process is not affected by camera lens orientation, focal length, viewing range, etc., making the assessment results more objective and accurate.

Based on the panoramic image, the method steps for calculating the Panoramic Green Visibility are proposed, including panoramic image acquisition, panoramic image projection transformation, and visible vegetation area calculation. The panoramic image obtained by the panoramic camera or related equipment is generally an equidistant cylindrical projection. The projection spread is a 2:1 rectangular image. In an isometric cylindrical projection, areas of isometric cylindrical projection do not have equal

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actual regions. To make the area of the panoramic image measurable, it is necessary to convert it into an equal-area cylindrical projection for calculation. This is done by first converting the original equidistant cylindrical projection to spherical coordinates and then converting the spherical coordinates to the equal-area cylindrical projection.

Once the panorama image has been converted to an equal-area cylindrical projection, the projected areas of its elements can be measured directly and their relative areas obtained. The ratio of the area of each component in the equal-area cylindrical projection image is used to calculate the Panorama Green Visibility, Panorama Sky Visibility, and Panorama Paved Visibility, which are calculated using the following formulae.

Panorama Green Visibility = (area of vegetation in the equal-area cylindrical projection image/total area of the equal-area cylindrical projection image) * 100%.

Panoramic Sky Visibility = (area of sky in the equal-area cylindrical projection image/total area of the equal-area cylindrical projection image) * 100%

Panoramic Paving Visibility = (area of paving in equal-area cylindrical projection image/total area of equal-area cylindrical projection image) * 100%

The area of vegetation in the projected image is usually calculated using the grid method. In this study, Adobe Photoshop image processing software set thresholds based on RGB channels and filter to extract their color pixel information for calculation as a quantitative part of the landscape elements.

2.3 Procedure

The survey was conducted from 5 July to 21 July 2021 from 13: 30-15: 30, in clear weather, during a season of maximum vegetation growth and bird and insect activity. The average temperature, wind, and air quality index (PM2.5 index [42]) during the experiment ranged from 22-29℃, 2-3 degrees, and 28-83μg/m3, respectively. The formal survey consisted of two parts: ECG data acquisition and fatigue status measurements. Each participant was assigned a intelligent ECG device. The device was connected to a smartphone and transmitted the uploaded data in real- time via Bluetooth. Their average age was 26±4 years, with 10 male and 14 female participants.

Participants were asked to follow a pre-determined path to a pre-determined 25 experimental sites. As they reached each pre-determined point in the park, the smart wearable device began recording ECG data over 5 minutes, after which they were required to complete a 14-item questionnaire (the Chalder

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Fatigue Scale [24]) to report their fatigue status. Using a combination of subjective questionnaires and objective physiological indicators provides a complete assessment of mental fatigue that is less prone to bias [43]. Table 1 shows the items of the fatigue scale. Afterward, and participants were asked to perform the AX-Continuous Performance Test (AX-CPT) for 45 minutes while ECG data were collected. The AX-CPT requires alertness, working memory, and response inhibition and has been used to induce mental fatigue in studies [44, 45]. At the beginning of the experimental task, subjects went through the entire process to ensure that they thoroughly understood the instructions [46].

The AX-CPT administered in this experiment was designed to induce participants to reach a state of mental fatigue and did not involve the evaluation of the subjects own attentional abilities; therefore, there were no evaluation criteria, nor any judgment of attentional deficit or otherwise, but only the completion of the task as correctly as possible within the allotted time.

After the AX-CPT, the fatigue scale was filled out again, after which. Participants were required to perceive the experimental site for 5 minutes [47], during which time changes in ECG data were recorded within these 5 minutes. At the same time, sound pressure levels were recorded at each measurement point using a sound level meter in an audio-visual environment. The sound pressure level meter was set to slow mode and A-weighting, and instantaneous data were read every 10 s. The sound level meter probe was located more than 1.0 m from any reflective surface and more than 1.2m from the ground [48]. The equivalent sound pressure level (LAeq) of the corresponding A-weighting is derived at each measurement location [47]. Camera equipment was used to obtain data on the visual environment at that time. Using these methods, we collected data on the audio-visual environment, data on the ECG during the experiment, and a sample of subjective scales.

TABLE I. Fatigue self-report assessment scale

Item	**Decribe**	**scale**
1	Do you feel have problems with tiredness ?	1-5
2	Do you need to rest more ?	1-5
3	Do you feel sleepy or drowsy ?	1-5
4	Do you have problems starting things ?	1-5
5	Do you start things without difficulty but get weak as you go on ?	1-5
6	Are you lacking in energy ?	1-5

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7	Do you have less strength in your muscles ?	1-5
8	Do you feel weak ?	1-5
9	Do you have difficulty concentrating ?	1-5
10	Do you have problems thinking clearly ?	1-5
11	Do you make slips of tongue when speaking ?	1-5
12	Do you find it more difficult to find the correct word ?	1-5
13	How is your memory ?	1-5
14	Have you lost interest in the things you used to do ?	1-5

2.4 Fatigue indicator data processing

In this study, Heart Rate Variability (HRV) indices were obtained from ECG for further analysis and assessment [49]. Studies have shown that the best performance for assessing changes in mental fatigue is obtained using 2-3 HRV indices. Of these, the NN.mean and PNN50 have the highest accuracy [41]. These two HRV indices are shown in Table 2.

TABLE II. HRV measures

Measure	**Formula**	**Unit**
NN.mean	$\frac{\sum_{i=1}^{N}(NN_i)}{N}$	ms
PNN50	$\frac{count(\lvert NN_{i+1} - NN_i \rvert) > 50ms}{N-1} \times 100\%$	/

After each participant had answered the 14 questions in Table 1, the range was from 1 (no sensation) to 5 (very severe). To determine the mental fatigue of the participants, a cut-off value of 3/4 of the total score was suggested in the study [24]. Therefore, samples with scores above 52.5 were identified as fatigued, and the rest were identified as non-fatigued, and the results are shown in Table 3 in conjunction with the HRV index.

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Table III. HRV indicators for non-fatigue and fatigue states

	Non-fatigue		Fatigue	
	Mean	**Var**	**Mean**	**Var**
NN.mean	0.8405	0.016	0.7099	0.019
PNN50	0.3083	0.034	0.2011	0.014

SPSS software [50]was used to conduct normality, correlation, and regression analyses on the visual environment, the auditory environment and the samples of NN.mean and PNN50. First, the Kolmogorov-Smirnov test was used to analyse the normality of the collected data. The results showed that the p values for the collected data Panoramic Sky Visibility (PSV), Panoramic Green Visibility (PGV), Panoramic Paving Visibility (PPV), and LAeq samples were all statistically significant with p values greater than 0.05. Second, Pearson's correlation was applied to calculate the relationship between audio-visual context and NN.mean or PNN50 responses and, T-tests ($p < 0.01$ and $p < 0.05$) were used to test for significant differences. Third, linear regression was used to establish the regression equation between the audio-visual context and the NN.mean or PNN50 responses. The significance of the regression equation was tested by ANOVA [51]. Fig. 1 illustrates the entire research process.

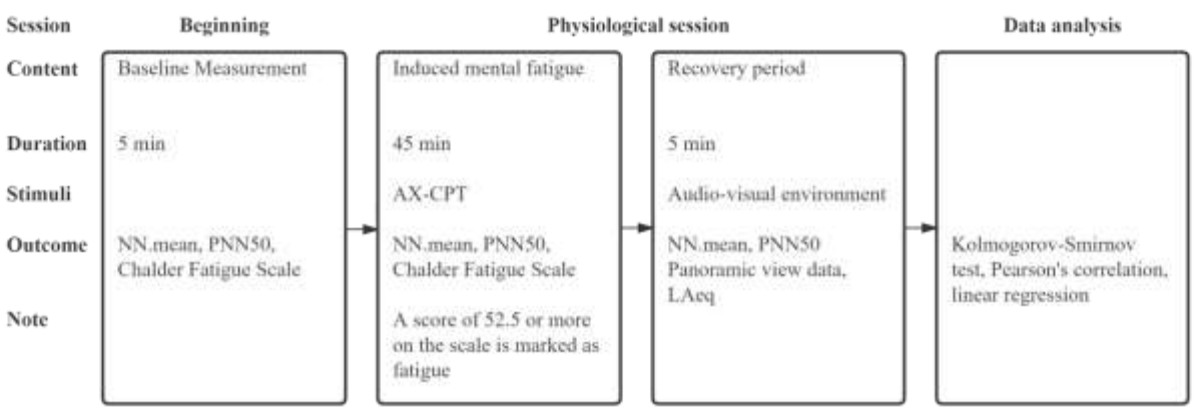

Fig 1: Research process

III. Data Analysis

The Pearson's correlation between the audio-visual environment of the city park and NN.mean and PNN50 are presented in Table 4. The results show that Panoramic Sky Visibility (PSV), Panoramic

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Paving Visibility (PPV), the ratio of Panoramic Paving Visibility to Panoramic Green Visibility (PG) and LAeq showed significant negative correlations with NN.mean, except for LAeq which had a significant level of $p > 0.01$ and a weak correlation (correlation coefficient R of 0.419). In terms of PNN50, Panoramic Sky Visibility (PSV), Panoramic Paving Visibility (PPV), and the ratio of Panoramic Paving Visibility to Panoramic Green Visibility (PG) were significantly negatively correlated. At the same time the correlation between LAeq and PNN50 was not significant ($p > 0.05$). For Panoramic Green Visibility (PGV) and the ratio of Panoramic Green Visibility to Panoramic Sky Visibility (GS), both indicators were significantly positively correlated with both NN.mean and PNN50 (correlation coefficient R with NN.mean were 0.881 and 0.811, $p < 0.01$, respectively; PNN50 correlation coefficient R were 0.901 and 0.847, $p < 0.01$).

Table IV. Pearson's correlation between audio-visual environment and heart rate variability

	PSV	**PGV**	**PPV**	**GS**	**PG**	**LAeq**
NN.mean	-0.879**	0.881**	-0.544**	0.811**	-0.681**	-0.419*
PNN50	-0.901**	0.892**	-0.560**	0.847**	-0.664**	-0.370

*indicates $p < 0.05$, **indicates $p < 0.01$.Panoramic Green Visibility (PGV), Panoramic Sky Visibility (PSV), Panoramic Paving Visibility(PPV), PGV: PSV (GS), PPV: PGV (PG),

According to the linear regression models of the audio-visual environment with NN.mean and PNN50 (as shown in Tables 5 and 6), the regression models established for PSV, PGV, and GS on NN.mean and PNN50 were significant ($p < 0.01$), and the coefficient of determination of these three visual element indicators on these two HRV indicators was higher than that of PPV and PG. The coefficient of determination of LAeq on NN.mean was only 0.175 and was not significantly correlated with PNN50.

Table V. Regression model of audio-visual environment and NN.mean

		Collinearity	**Unstandardized**		**Standardized Coefficients**	**Sig.^{a}**	**Sig.^{b}**
NN.mean		**VIF**	**Regression coefficient**	**Std.error**	**Beta**		
R^2=0.772 R^2(adj)=0.762	(Constant)		0.855	0.010		0.000**	0.000**
	PSV	1.000	-0.258	0.029	-0.879	0.000**	

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R^2=0.776 R^2(adj)=0.766	(Constant)		0.726	0.006		0.000**	0.000**
	PGV	1.000	0.164	0.018	0.881	0.000**	
R^2=0.296 R^2(adj)=0.265	(Constant)		0.862	0.028		0.000**	0.005**
	PPV	1.000	-0.241	0.078	-0.544	0.005**	
R^2=0.657 R^2(adj)=0.643	(Constant)		0.752	0.005		0.000**	0.000**
	GS	1.000	0.015	0.002	0.811	0.000**	
R^2=0.464 R^2(adj)=0.440	(Constant)		0.793	0.006		0.000**	0.000**
	PG	1.000	-0.007	0.002	-0.681	0.000**	
R^2=0.175 R^2(adj)=0.140	(Constant)		0.909	0.061		0.000**	0.037*
	LAeq	1.000	-0.002	0.001	-0.419	0.037*	

*indicates $p < 0.05$, **indicates $p < 0.01$. [a] Significance of regression coefficient, [b] Significance of regression equation, VIF: Variance Inflation Factor.

Table VI. Regression model of audio-visual environment and PNN50

		Collinearity	**Unstandardized**		**Standardized Coefficients**	**Sig.[a]**	**Sig.[b]**
PNN50		**VIF**	**Regression coefficient**	**Std.error**	**Beta**		
R^2=0.811 R^2(adj)=0.803	(Constant)		0.281	0.005		0.000**	0.000**
	PSV	1.000	-0.146	0.015	-0.901	0.000**	
R^2=0.795 R^2(adj)=0.786	(Constant)		0.208	0.003		0.000**	0.000**
	PGV	1.000	0.091	0.010	0.892	0.000**	
R^2=0.313	(Constant)		0.285	0.015		0.000**	0.004**

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R^2(adj)=0.283	PPV	1.000	-0.136	0.042	-0.560	0.004**	
R^2=0.718 R^2(adj)=0.706	(Constant)		0.222	0.003		0.000**	0.000**
	GS	1.000	0.009	0.001	0.847	0.000**	
R^2=0.441 R^2(adj)=0.417	(Constant)		0.245	0.003		0.000**	0.000**
	PG	1.000	-0.004	0.001	-0.664	0.000**	
R^2=0.137 R^2(adj)=0.099	(Constant)		0.301	0.034		0.000**	ns
	LAeq	1.000	-0.001	0.001	-0.370	ns	
*indicates $p < 0.05$, **indicates $p < 0.01$. [a] Significance of regression coefficient, [b] Significance of regression equation, VIF: Variance Inflation Factor, and ns $p > 0.05$ (no significance)							

Since PSV, PGV, and PPV have a strong covariance, the ratio of Panoramic Green Visibility to Panoramic Sky Visibility (GS) and the ratio of Panoramic Paving Visibility to Panoramic Green Visibility (PG) were introduced. There is no significant covariance between GS and PG, and their variance inflation factor (VIF) < 10 makes the established multiple linear regression model more reliable. At the same time, GS and PG reflect the combined distance of the participants' in different locations in the same space from the surrounding landscape. Their multiple linear regression models with NN.mean and PNN50 are shown in Tables 7 and 8. GS and PG have a high coefficient of determination for either NN.mean or PNN50. The influence of GS on both was dominant, with beta weights of 0.632 and 0.687, respectively.

Table VII. Multiple regression models for visual environment and NN.mean

		Collinearity	**Unstandardized**		**Standardized Coefficients**	**Sig.[a]**	**Sig.[b]**
NN.mean		**VIF**	**Regression coefficient**	**Std.error**	**Beta**		
	(Constant)		0.767	0.006		0.000**	0.000**
R^2=0.780 R^2(adj)=0.760	GS	1.260	0.012	0.002	0.632	0.000**	
	PG	1.260	-0.004	0.001	-0.394	0.002**	
*indicates $p < 0.05$, **indicates $p < 0.01$. [a] Significance of regression coefficient, [b] Significance of							

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regression equation.

Table VIII.A multiple regression model of the visual environment and PNN50

PNN50		Collinearity VIF	Unstandardized Regression coefficient	Unstandardized Std.error	Standardized Coefficients Beta	Sig.[a]	Sig.[b]
	(Constant)		0.230	0.003		0.000**	0.000**
R^2=0.816 R^2(adj)=0.799	GS	1.260	0.007	0.001	0.687	0.000**	
	PG	1.260	-0.002	0.001	-0.352	0.002**	

*indicates $p < 0.05$, **indicates $p < 0.01$. [a] Significance of regression coefficient, [b] Significance of regression equation.

IV. Discussion

In this study, ECG data obtained using a smart wearable device was combined with an audio-visual environment in an urban park. This is more convenient for the general public, So more data can be obtained in future experiments to reduce bias. It avoids the invasiveness of the laboratory environment for the testers and compensates for the inaccuracy of not being able to simulate the actual environment in the laboratory fully.

In terms of the visual environment, the panoramic view method was used, avoiding the subjectivity and uncertainty of the data obtained by the traditional way, which relied on indicators such as the angle of the photograph and the focal length of the lens. In terms of the auditory environment, the representative LAeq was chosen to provide a more accurate representation of the physical acoustic environment within the environment.

In terms of selecting indicators of mental fatigue, previous research has shown that the NN.mean and PNN50 are physiologically objective indicators of changes in participants' mental fatigue. The choice of real-time objective physiological indicators also avoids some of the disadvantages of using only subjective questionnaires. However, there is no research to confirm that NN.mean and PNN50 can be

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characterized as mental fatigue when they reach a certain level, but only as an indication of trends in mental fatigue in their own right. Studies have shown that NN.mean and PNN50 are negatively correlated with mental fatigue [41], and Table 3 is consistent with this finding. Therefore, in this study, the attempt to quantify the best values obtained for each audio-visual element to achieve the best mental fatigue recovery is not yet achievable. As future medical research develops, more refined quantitative analysis studies will be needed in the future.

The most significant contribution of this study is that it provides a new, more objective, and accurate way of exploring the impact of urban parks on recovery from mental fatigue, and can quantify the extent to which individual elements of the audio-visual environment affect participants.

There are many variable factors in human response. In this study, the participants were all young people. Other age groups have different physiological states than young people, which may affect the relationship between the audio-visual environment, and mental fatigue. Seasonal differences may also lead to the different audio-visual environments, and to avoid seasonal effects, this study was conducted in only one season. Considering population characteristics and seasonality is essential in creating audio-visual environments in urban parks that promote recovery from mental fatigue. Therefore, further analysis is needed in future studies.

V. Conclusions

Based on this new approach, the following conclusions were obtained.

Firstly, in terms of the auditory environment, the correlation between LAeq and PNN50 was not significant. The coefficient of determination for NN.mean was small, suggesting that changes in LAeq in the park environment would hardly affect participants recovery from mental fatigue in a short period.

Secondly, PSV and PGV, had a more significant coefficient of determination than PPV for both NN.mean and PNN50. PGV showed a significant positive correlation with these two ECG indicators, while PSV and PPV showed a significant negative correlation with these two ECG indicators. This suggests that places with more artificial paving and open spaces (e.g., squares) are not conducive to participants' recovery from mental fatigue.

Finally, by the nature of the ratio of Panoramic Green Visibility to Panoramic Sky Visibility (GS) and Panoramic Paving Visibility to Panoramic Green Visibility (PG), these two items are not only panoramic data within the field of view, but also a description of the distance to the scene from the different locations in which the participants participated in the same spatial environment. Their effect on the two indicators of mental fatigue, NN.mean and PNN50, suggests that better recovery from mental fatigue can be achieved in urban parks closer to vegetation and with higher levels of enclosure. This may also be related to the lower temperatures perceived by the body in areas close to vegetation compared to areas with more paving and further away from vegetation, and needs further study.

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