Acta Acustica 2025, **9**, 7
© The Author(s), Published by EDP Sciences, 2025
https://doi.org/10.1051/aacus/2024087

Available online at:
https://acta-acustica.edpsciences.org

SCIENTIFIC ARTICLE OPEN ACCESS

Influence and prediction mechanisms for discomfort and memory disturbance due to structure borne sound from a metro masked with fountain sound

Qiaochu Wang[1], Wang Hongwei[2,*], Yangsheng Cai[1], Yang Zhang[1], and Chenxi Yang[2]

[1]School of Architecture and Urban Rural Planning, Fujian University of Technology, No. 69, Xuefu South Road, Shangjie Town, Minhou County, Fuzhou, Fujian 350118, China

[2]School of Architecture, South China University of Technology, State Key Laboratory of Subtropical Building Science, No. 381, Wushan Road, Guangzhou, Guangdong 510640, China

Received 22 July 2024, Accepted 6 December 2024

Abstract – Previous studies suggested that introducing fountain sound could mitigate the discomfort and memory disturbance caused by structure borne sound from a metro, and proposed the prediction models for the discomfort after mitigation. However, these studies failed to identify the primary, secondary and significant influencing factors on the discomfort after mitigation, which hindered the proposal of optimal masking strategy and undermined the scientific validity of models. Additionally, previous analyses overlooked the primary, secondary and significant influencing factors on the memory disturbance after mitigation and lacked prediction model for it. Therefore, this study explored these aspects further. Based on auditory experiments, using partial least squares model and prediction model, this study found that considering total impact degree, the discomfort was predominantly influenced by the subjective loudness. However, the sound levels were the most important factors in determining the memory disturbance. The signal-to-noise ratio significantly influenced the discomfort but had no significant impact on the memory disturbance. Moreover, the subjective loudness emerged as the most effective predictor of the discomfort. While predicting the memory disturbance predominantly depended on the sound levels, and among the prediction models based on the sound levels, the predictive effectiveness of the energy summation model was comparable to that of the independent effects model. Furthermore, as global equivalent A-weighted sound level increased, the mitigation effect on discomfort became more evident, but its effectiveness in mitigating the memory disturbance gradually decreased. These conclusions could provide optimal strategies for enhancing such masking effects, and more effective prediction tools for such effects.

Keywords Structure borne sound from a metro, Fountain sound, Sound masking, Subjective loudness, Mechanism analysis

1 Introduction

To mitigate the adverse effects of noise on people, researchers put forward two main approaches for noise impact control: one being the reduction strategy, the other the addition strategy [1, 2]. In indoor environments, conventional strategies for reducing noise levels, such as installing insulation walls, are often expensive or inconvenient to implement. In contrast, soundscape practitioners explored the potential of integrating pleasant sounds, an approach called sound masking, as a means of achieving effects comparable to traditional noise level-reduction methods [3, 4]. This optimization approach can be achieved by broadcasting pleasant electroacoustic sounds in indoor environments, which is not only easy to conduct but also cost-effective. With the continuous expansion of metro network and the increasing metro speed, the issue of structure borne sound inside building induced by metro operation has become increasingly prominent, and complaints from the public about such noise are also increasing [5]. Therefore, there is an urgent need to explore more effective methods of mitigating the negative effects due to structure borne sound from a metro (abbreviation "metro sound" in the following descriptions apart from conclusions) through the addition of pleasant sound, thereby minimizing the disturbances to the daily lives of residents around metro lines in an easy manner.

*Corresponding author: wanghw@scut.edu.cn

Extensive research proposed the strategies to improve the reactions caused by road traffic noise through the addition of water sounds [6–12]. Road traffic noise primarily originates from the friction between road and wheel, as well as exhaust noise, and this noise is transmitted through air. On the other hand, metro sound originates from vibrations caused by the friction between the metro and the track. These vibrations are transmitted upwards through building structure and accordingly radiate secondary sound. Metro trains and road vehicles differ significantly in vehicle type, operating speed, and load capacity. Similarly, metro track material and road surface have their unique characteristic. These differences in sound generation and transmission mode may lead to difference in the acoustic feature of metro sound and road traffic noise. Additionally, several empirical models were developed to predict human reaction to concurrent exposure to multiple sound sources. These include the energy summation model [13], the independent effects model [13], the energy difference model [13], the response-summation model [14], the summation and inhibition model [15], the annoyance equivalents model [16], and the dominant source model [17]. However, these models were commonly used to test their validity for predicting the negative reactions caused by the combinations of unwanted sounds [15–19], only a few recent studies examined if they can predict the negative reactions resulting from the combinations of wanted and unwanted sounds [6, 19]. Furthermore, the previously proposed models mainly focused on predicting the negative perceptions such as annoyance and dissatisfaction [6, 17–20], but their applicability to assessing activity disturbance, another type of negative reaction, remains uncertain.

Although Wang et al. demonstrated that the introduction of fountain sound can mitigate the discomfort [21] and memory disturbance [22] caused by metro sound, their analysis had limitations in elucidating the mechanisms following the mitigation of negative reactions. Specifically, regarding the discomfort after mitigation, Wang et al. primarily relied on line graphs depicting the mean discomfort levels under different influencing factors, to assess the independent effects of various objective acoustic parameters. However, there are several issues to consider: Firstly, besides objective acoustic parameters, subjective factors such as subjective loudness may also significantly affect the discomfort after mitigation, but the previous study did not consider the mechanism of these subjective factors. Secondly, Wang et al. overlooked the potential impact of interactions between multi-dimensional influencing factors, which may have significant effects on the discomfort after mitigation. Lastly, Wang et al. failed to distinguish between primary, secondary and significant factors influencing the discomfort after mitigation. Due to these limitations, the prediction models established by Wang et al. for assessing the discomfort after mitigation [20] may not be scientific enough. Regarding the memory disturbance after mitigation, in addition to the aforementioned research limitations, the previous study failed to put forward the prediction models for the memory disturbance after mitigation. To develop more scientific prediction models and optimal strategies for enhancing the masking effects, future research should address the aforementioned missing areas, considering both the discomfort after mitigation and memory disturbance after mitigation.

Given all these factors, previous studies lacked analyses of the primary, secondary and significant influence factors for discomfort after mitigation and memory disturbance after mitigation, achieved by adding fountain sound to metro sound, as well as the construction of more scientific and valid prediction models based on these. Accordingly, through the applications of partial least squares (PLS) model, considering the potential subjective and objective influencing factors of discomfort after mitigation and memory disturbance after mitigation, as well as the interaction mechanisms between these factors, this study identified the primary, secondary, and significant factors influencing the discomfort and memory disturbance. Based on these significant influencing factors, separate prediction models were developed for the discomfort and memory disturbance, enabling the determination of the impacts of various factors, and the optimal models with the greatest predictive accuracy were selected to more precisely predict the masking effects. The aforementioned analytical findings formed the basis for a more comprehensive and scientific evaluation of the influence and prediction mechanisms after mitigating these two negative reactions. The aim of this study is to provide optimal strategies for enhancing the masking effects and develop more effective tools to predict such effects.

2 Method

2.1 Collection of acoustic stimuli

This study aimed to collect a typical metro sound sample in preparation for a series of auditory experiments. A framed high-rise commercial office building, situated near the Guangzhou Metro Line 4 and susceptible to the impact of metro operation, was selected as the site for collecting binaural samples of metro sound. Guangzhou Metro Line 4 represents a typical metro trunk line in China, operating at an average speed of approximately 50 km/h and capable of attaining a maximum speed of nearly 90 km/h. The sound sample collection site is adjacent to a curved metro track, characterized by a monolithic roadbed, which is positioned next to an island platform. Furthermore, this metro track is located within an underground tunnel, primarily constructed of reinforced concrete, with the surrounding soil mainly comprising silty and sandy clay.

When metro trains pass through the adjacent tunnel of investigated building, people would experience notable metro sound on the lower floors inside the building, characterized by a rumbling sound accompanied by the vibrations of floor, wall and indoor object. To minimize the disturbances from other indoor noise sources

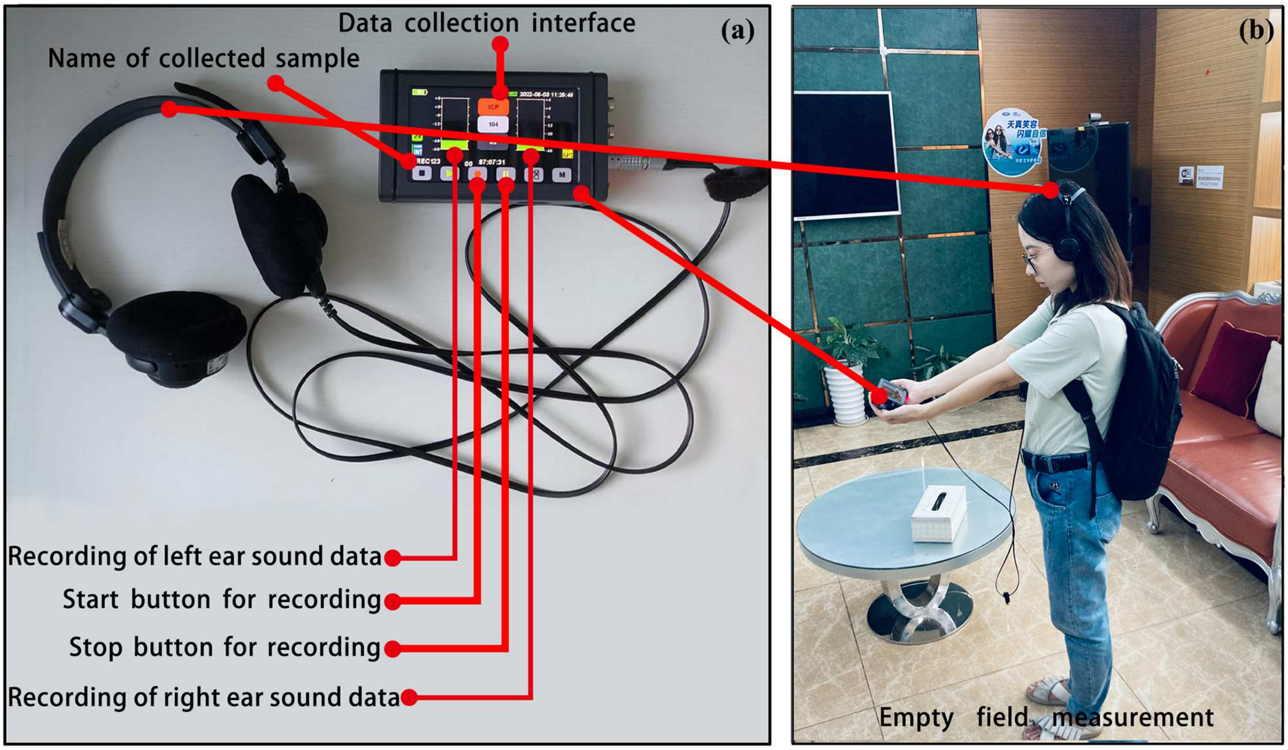

Figure 1. Gathering the binaural samples of metro sound (a) using a handheld binaural recorder (b).

during data collection, the binaural samples of metro sound were specifically collected during the morning peak hours (7:00 a.m. to 9:00 a.m.). During this period, with a low occupancy rate, the condition was similar to that of data collection in an empty field, and there was nearly no disturbance from indoor noise sources. Furthermore, there are no other railway lines around the data collection site, effectively shielding it from railroad noise, and the data collection site is surrounded by other usable spaces, effectively shielding it from outdoor road traffic noise. This ensured that the gathered data was primarily attributed to the sound due to structural vibrations of the floors and walls within the office, which were generated by metro operation, while minimizing disturbances from other indoor and outdoor noise sources that might be transmitted through flank transmission or atmospheric sound propagation.

For the purpose of capturing binaural samples of metro sound, a handheld binaural artificial head, specifically the SQuadriga III brand, was utilized. This set of equipment comprises two parts: one is the sound sample storage and analysis equipment, which boasts four channels and offers the capability to connect to external device. The other part of equipment consists of binaural recording headphones, used for recording, that were connected to two channels of the sound sample storage and analysis equipment for capturing the sounds from both left and right ears. Prior to recording, the sampling rate must be set; in this study, it was configured at 44 100 Hz, which is accurate enough for subjective listening [21]. Once the start button is pressed, the equipment begins recording sounds at both ears, displays the recording duration in real-time, and then store sound samples as audio files in head data and wave formats. In addition to its recording, storage and analysis functions, this set of equipment is also equipped with a playback function, allowing for the testing of the quality of collected sound sample through playback. Prior to the noise recording, calibration was conducted to ensure the measurement accuracy of artificial head. During the field collection, according to the measurement standards of indoor noise level [23–25], the height of the artificial head was set at least 1.2 m from the ground, and the distance between the artificial head and the nearest vertical plane was at least 1.5 m, and it was positioned at least 1 m away from the operator's torso. The handheld binaural artificial head was held in the center of the room, facing the main usage direction, to continuously record the environmental noise (Fig. 1).

Since metro sound can be clearly heard at the sound sample collection site, this study recorded its approximate start time. Based on the recorded start time and the sound wave file collected using the artificial head, the signal of metro sound was identified. Given the intermittent nature of metro sound and its typical duration of approximately 10 s in indoor environments (encompassing the entry and exit processes of metro) [5], a 10 s sample of metro sound was extracted from the collected sound sample for subsequent adjustment of listening sample. Furthermore, minor differences were observed in metro sound data between the left and right ears, which were primarily attributed to the positioning of artificial head,

Table 1. The binaural L_{Aeq} of two selected sounds and their combinations used in auditory experiments.

Combined sound (dBA)	55	55	55	55	55	55	60	60	60
Fountain sound (dBA)	45.5	48	50.2	52	53.2	54	50.5	53	55.2
Metro sound (dBA)	54.5	54	53.2	52	50.2	48	59.5	59	58.2
SNR (dBA)	−9	−6	−3	0	3	6	−9	−6	−3
Combined sound (dBA)	60	60	60	65	65	65	65	65	65
Fountain sound (dBA)	57	58.2	59	55.5	58	60.2	62	63.2	64
Metro sound (dBA)	57	55.2	53	64.5	64	63.2	62	60.2	58
SNR (dBA)	0	3	6	−9	−6	−3	0	3	6

resulting in the difference in sound reflection pattern from the walls.

In selecting water sound as the masking sound, this study chose fountain sound, which is a typical water body type [26] and commonly encountered in daily life. The fountain sound sample was sourced from a professional audio website [27] that offers a vast array of high-quality audio samples for users to download and utilize freely. The fountain sound sample obtained from this website featured identical left and right ear listening data, and its sampling rate aligned with the recorded metro sound at 44 100 Hz. The fountain sound sample exhibited a continuous spraying effect, emitting a sound similar to "gurgling". Given that the duration of metro sound was set as 10 s, the fountain sound (masking sound) sample was truncated to match this length of 10 s. Consequently, each combined sound sample comprised 10 s of metro sound and 10 s of fountain sound.

2.2 Design of auditory experiment

Prior to the auditory experiments, the measurements of metro sound level were conducted in some high-rise office buildings. Based on over 40 groups of measurement data in these buildings, it was found that the exposure levels in areas easily affected by metro operations were generally between 50 and 65 dBA. Referring to one previous study [6], three higher and equally spaced equivalent A-weighted sound levels (L_{Aeq}) of metro sound were selected as binaural L_{Aeq} for combined sound, namely 55, 60, and 65 dBA, where binaural L_{Aeq} is defined as the energetic average of L_{Aeq} data from the left and right ears [28–30]. To more accurately simulate the indoor metro sound environment, the L_{Aeq} difference between the left and right ears of metro sound during collection was maintained in the calculation.

Drawing from one previous study [6], the range of SNR (Signal-to-Noise Ratio) variation was set, ranging from −9 to 6 dBA with a change interval of 3 dBA. SNR is the difference between binaural L_{Aeq} of fountain sound and binaural L_{Aeq} of metro sound, where a positive value indicates that binaural L_{Aeq} of fountain sound is higher than that of metro sound, and vice versa. Based on this, 18 (calculated as 3×6) sets of combined sound samples containing metro sound and fountain sound were generated. Table 1 showed the binaural L_{Aeq} of two selected sounds and their combinations, which were used in auditory experiments. A dual-channel playback mode was set in the computer audio playback software, where one channel was used to play the binaural samples of metro sound, and the other channel was used to play the binaural samples of fountain sound (featuring identical data for both ears). By connecting the headphones to the computer, the subjects could clearly hear the binaural samples of combined sound through the headphones.

In this study, the auditory experiments were carried out utilizing Sennheiser's HD580 headphones, HD580 headphone model from the brand Sennheiser. This particular model features a frequency response spanning from 12 Hz to 38 kHz, coupled with a nominal impedance of 300 Ω. To minimize the influence of the headphones' frequency response on the listening data, frequency response calibrations were performed. Specifically, an artificial head was employed to capture the time-domain data of binaural sine sweep signals, which were generated using Audition software and played back through the headphones. The captured time-domain data was then convolved with the inverse filter data of sine sweep signals to ascertain the impulse responses of the headphones. Following that, both the sample of metro sound and the sample of fountain sound underwent convolution with the inverse filtered data from the headphone impulse response prior to L_{Aeq} adjustment. These steps ensured that the listening samples could reproduce the on-site measurement data and downloaded data to the greatest extent.

Given that noise can elicit a range of negative emotions in people, previous studies have thus established a multi-dimensional noise reaction assessment system to comprehensively analyze these adverse effects. This system consists of several mutually independent indicators for evaluating reaction, including, but not limited to, three dimensions [31]. These dimensions were chosen because they basically cover the typical types of negative reactions commonly experienced in daily life. The first dimension captures the uneasiness caused by noise, encompassing both individuals' behavioral responses and multi-level emotional perceptions [31]. The second dimension measures the sound intensity perceived by human ear, which is typically positively correlated with negative perception, indicating that louder sound tends to evoke stronger negative perception [32]. The third dimension assesses the degree of disturbance that noise causes to people's daily activities [33]. This study selected three representative indicators from the aforementioned dimensions: discomfort, subjective loudness, and the disturbance of learning activity. These indicators have been widely used in various studies on noise reaction evaluation [34–36]. Since the objective of this study was to analyze the negative psychological impact and disturbances in daily activities resulting from noise, discomfort and disturbance to learning activity were specifically chosen as targeted evaluation indicator. Subjective loudness was considered as a potential contributing factor to these two targeted reactions. As for the selection of evaluation indicator for disturbance to learning activity, one previous study found that, in an environment with the same L_{Aeq} of metro sound, memory disturbance was the most significantly affected, compared to disturbances in calculation and judgment activities [22], and therefore was selected as the aspect to optimize the disturbance to learning activity.

2.3 Performance of auditory experiment

In order to investigate the levels of multi-dimensional negative reactions caused by the combination of metro sound and fountain sound, a series of reaction level investigations were conducted in an auditory test booth (with dimensions of approximately 4 m in length, 8 m in width, and 3 m in height) at South China University of Technology. The background noise level in this auditory test booth is extremely low, with L_{Aeq} of approximately 25 dBA. To ensure the recruitment of subjects with normal hearing, two aspects of work were conducted prior to the auditory experiments. On the one hand, during the recruitment process, young college students known to possess normal hearing capabilities were targeted. Prior to each auditory experiment, the subject confirmed that they could normally attend classes and communicate in daily life without undergoing medical treatment for hearing issues. On the other hand, each subject was instructed to listen to two distinct types of sound samples: metro sound and fountain sound. They all attested to having encountered these two types of sounds in real-life situations and being well-acquainted with these sound sources. Furthermore, when each sound sample changed by 5 dBA, which is a widely recognized acoustical increment in acoustical research that leads to a change in the perceived sound level by individuals [37, 38], they were able to distinctly perceive the alteration in sound level. Consequently, although pure tone tests were not administered to evaluate the subjects' hearing status, the aforementioned procedures substantially assured that the subject group indeed had normal hearing.

Before the experiments began, every subject was required to sign an experimental consent form that addressed ethical considerations. The form emphasized that the experiment was solely focused on investigating personal reactions, that no personal information would be collected, and that the research results would be utilized exclusively for academic purposes. During each auditory experiment, only one subject was involved, sitting before a desk to simulate daily learning conditions. Since all subjects were non-experts in acoustics, they underwent training prior to the official subjective survey to ensure accurate understanding and appropriate responses during the auditory experiments. Ahead of the start of experiments, all combined sound samples were randomly numbered to ensure an unbiased order, and these were presented to each subject for multi-dimensional reaction investigations. Specifically, the investigations were divided into two parts. The first part focused on multi-dimensional negative perceptions. After each combined sound sample was played, each subject was required to rate the subjective loudness level and discomfort level due to each combined sound sample using a five-point scale [29, 39, 40]. The subjective loudness scale measured the perceived sound intensity by human ear, with five levels ranging from "not noisy at all" to "slightly noisy", "moderately noisy", "very noisy", and "extremely noisy". The discomfort scale reflected the degree of uncomfortable reaction caused by sound, ranging from "not uncomfortable at all" to "slightly uncomfortable", "moderately uncomfortable", "very uncomfortable" and "extremely uncomfortable".

The second part of the experiment investigated the level of memory disturbance. This study selected four randomly presented three-digit numbers for each subject to memorize within 10 s when each combined sound sample was played. The reasons for choosing this memory content are as follows. On the one hand, to minimize the impacts of subjects' knowledge background and logical ability on the assessment of memory disturbance level, the simplest possible numbers were chosen for memorization. Given that subjects see these numbers, they would be able to commence mechanical memorization immediately. On the other hand, prior to the auditory experiments, a series of preliminary tests were conducted. It was discovered that the majority of subjects were capable of recalling up to four three-digit numbers during a 10 s exposure to each combined sound sample. This indicates that subjects would persist in memory-related task throughout the entire listening period, preventing memory termination due to inadequate memory content. Consequently, this ensures that the subjects could experience the disturbance of the entire combined sound sample on memory activity. Following one previous study [36], the specific experimental steps for defining the disturbance degree are as follows: During the playback of each combined sound sample lasting for 10 s, each subject was required to attempt to memorize four randomly presented three-digit numbers. Immediately after the playback of each combined sound sample, each subject had to stop the memory task, recall, and write down the four three-digit numbers they had just memorized. Following this, each subject was asked to rate the level of disturbance experienced during this memory task using a five-point scale, ranging from "not disturbed at all" to "slightly disturbed", "moderately disturbed", "very disturbed", and "extremely disturbed".

This study recruited 79 subjects to take part in the auditory experiments, collecting a total of 1422 questionnaires for the investigation of discomfort and subjective loudness caused by the combination of metro sound and fountain sound. Additionally, an equal number of questionnaires, filled out by the same subjects, were collected for the investigation of memory disturbance. The subject group consisted of 40 males and 39 females, with the majority aged between 20 and 24, followed by those aged 25 to 29, and a few aged between 35 and 40. Regarding their educational background, all subjects possessed a high education level, including 6 undergraduate candidates, 62 master's degree candidates, and 11 doctoral candidates.

This study conducted the reliability and validity tests on the collected multi-dimensional negative reaction data (discomfort, subjective loudness and memory disturbance) elicited by the combined sounds. The results revealed that the Cronbach's Alpha reliability coefficient surpassed 0.7, the KMO validity coefficient was close to 0.6, and the significance level of Bartlett's test of sphericity was below the threshold of 0.05. This signifies that the collected subjective evaluation data exhibited high reliability, validity, and good internal consistency, thus providing a dependable foundation for further in-depth analysis.

2.4 Prediction model for combined sound reaction

Previous studies suggested different methods for evaluating negative reactions to noise, including psychophysical model, artificial neural network model, decision tree model, etc. Psychophysical model was selected in this study to preliminarily predict negative reactions to combined sounds. One previous study [13] proposed three psychophysical models which were widely used for predicting combined sound reaction, namely the energy summation model, the independent effects model, and the energy difference model. These models correlate people's reaction levels with one or more objective acoustic parameters. Based on the acoustic characteristics of various combined sound samples, numerous studies assessed the applicability of these models and selected a series of optimal prediction models from among them [6, 16, 19]. Drawing on the previous studies and utilizing the three psychophysical models, this study aimed to establish the prediction models for people's multi-dimensional reactions to the combination of metro sound and fountain sound, which could be used to assess the impacts of various factors on these reactions. Additionally, this study aimed to determine the optimal prediction models with the greatest predictive accuracy, in order to enable more precise predictions of the masking effects on these adverse reactions. This section briefly introduces these three models.

2.4.1 Energy summation model

This model indicates that reaction level (P_{T}) is due to global L_{Aeq}:

$$P_{\mathrm{T}} = aL_{\mathrm{T}} + b \tag{1}$$

where P_{T} represents the reaction level resulting from combined sound, and L_{T} denotes global L_{Aeq}, representing the total energy of separate sounds. This model is based on the theory that the reaction level caused by combined sound can be estimated by energy summation. This means that the capacity to evoke specific reaction is identical across combined sounds, a claim that has been frequently questioned [13, 41].

2.4.2 Independent effects model

This model indicates that reaction level (P_{T}) is due to separate sounds:

$$P_{\mathrm{T}} = a_1L_1 + a_2L_2 + b \tag{2}$$

where P_{T} represents the reaction level from combined sound, and $L_1, L_2, \ldots, L_n$ are the L_{Aeq} values of separate sounds. This model posits that reaction level is determined by the sound levels of separate sounds, employing a linear regression framework to quantify the impact of each separate noise level. Multiple studies proved that this model was the best in terms of prediction accuracy [6, 19].

2.4.3 Energy difference model

This model indicates that reaction level (P_{T}) is due to global L_{Aeq} and the difference in L_{Aeq} between separate sounds:

$$P_{\mathrm{T}} = aL_{\mathrm{T}} + b\,|L_1 - L_2| + c. \tag{3}$$

The model incorporates the difference in L_{Aeq} between two separate sounds as a correction factor based on the energy summation model, to reflect the combined influence of total sound energy and the difference in sound energy on the reaction level to combined sound. However, this model can only be applied in the conditions involving two types of sound sources. Several studies failed to provide evidence supporting the applicability of this model [42–45].

2.5 PLS model

PLS is a comprehensive multivariate data analysis method that combines the strengths of various statistical techniques, including multiple linear regression, principal component analysis, and canonical correlation analysis. Within its analytical framework, PLS employs an iterative approach to thoroughly investigate the impact of independent variables on the dependent variable and uncover the intricate interactions between independent variables. By exploring potential causal relationships

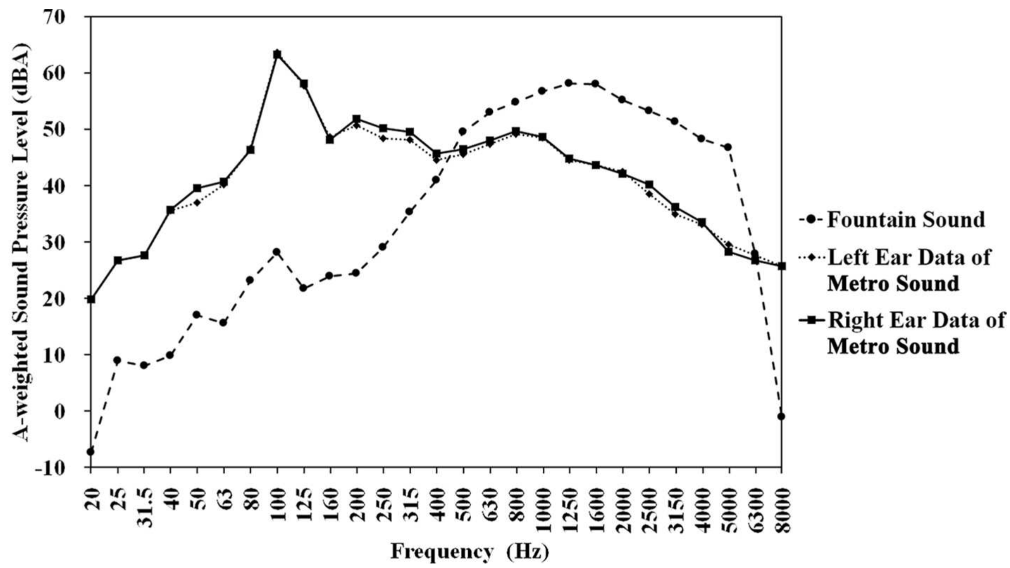

Figure 2. Spectra of binaural metro sounds and monaural fountain sound separately under a binaural L_{Aeq} of 65 dBA.

between the dependent variable and a set of independent variables, PLS enhances the depth and comprehensiveness of problem analysis. This evaluation technique is widely recognized for its precision and reliability [46], finding broad applications in diverse research fields [47–50].

The study employed Smart PLS 4.0 software to develop PLS models, focusing separately on the discomfort after mitigation and memory disturbance after mitigation. Smart PLS is a Java-based application specifically designed for PLS statistical analysis. The detailed data analysis steps in this study are outlined below. Firstly, the analysis data was imported into the Smart PLS 4.0 software. Then, within the software interface, a prediction path model was created. Subsequently, a PLS calculation was performed using PLS-SEM algorithm, generating a PLS prediction path diagram. Through the reports exported from the path diagram, information such as effect size and loading coefficient was obtained. To further validate the significance of prediction path, the Bootstrap calculation was conducted, resulting in a significance test path diagram that indicates whether the influence was statistically significant. With these data, the detailed analyses of influence degree of different independent factors can be conducted.

When outputting PLS calculation results, index values intended to examine the model's reliability and validity were also obtained. These indices include three key metrics: Average Variance Extracted (AVE), Composite Reliability, and Cronbach's Alpha. AVE evaluates the explanatory power of latent variables that are derived from observed variables. Typically, an AVE exceeding 0.5 denotes adequate explanatory capability. Composite Reliability assesses the consistency of measurement values associated with each latent variable, a value of 0.7 or above indicates strong consistency. Cronbach's Alpha evaluates the reliability of model, and generally, a score above 0.65 is considered to indicate the good reliability of model [45].

2.6 Acoustic characteristics of sound stimuli

Due to differences in the data from the left and right ears in the binaural samples of metro sound, while the fountain sound data remained identical for both ears, Figure 2 presents the spectral curves of binaural samples of metro sound and a monaural sample of fountain sound, separately measured at a binaural L_{Aeq} of 65 dBA. For the binaural metro sounds, the spectral curves of A-weighted sound pressure level (SPL) for both ears exhibited a high degree of similarity. Their A-weighted SPLs rose significantly from 20 Hz and peaked at 100 Hz. Subsequently, as frequency increased, they generally displayed gradual downward trends. In contrast, the A-weighted SPL of fountain sound was significantly lower than those of binaural metro sounds in the low-frequency band ranging from 20 to 200 Hz. Additionally, the A-weighted SPL of fountain sound fluctuated within the low-frequency band, peaking at 1600 Hz, and then gradually decreased, eventually dropping significantly in the 5–8 kHz frequency band.

Figure 3 displays the normalized time signals for both binaural metro sounds and monaural fountain sound. It can be seen that the time-domain signals of metro sound in the left and right ears were very close. That is, the binaural levels of metro sound (Fig. 3a) basically gradually escalated as time elapsed, nearly reaching their peaks basically at the intermediate section of the time domain. Subsequently, as time progressed further, the binaural levels basically gradually decreased. Conversely, the level of fountain sound (Fig. 3b) exhibited intermittent peaks over time, while in other instances, the variation in fountain sound level was not significant.

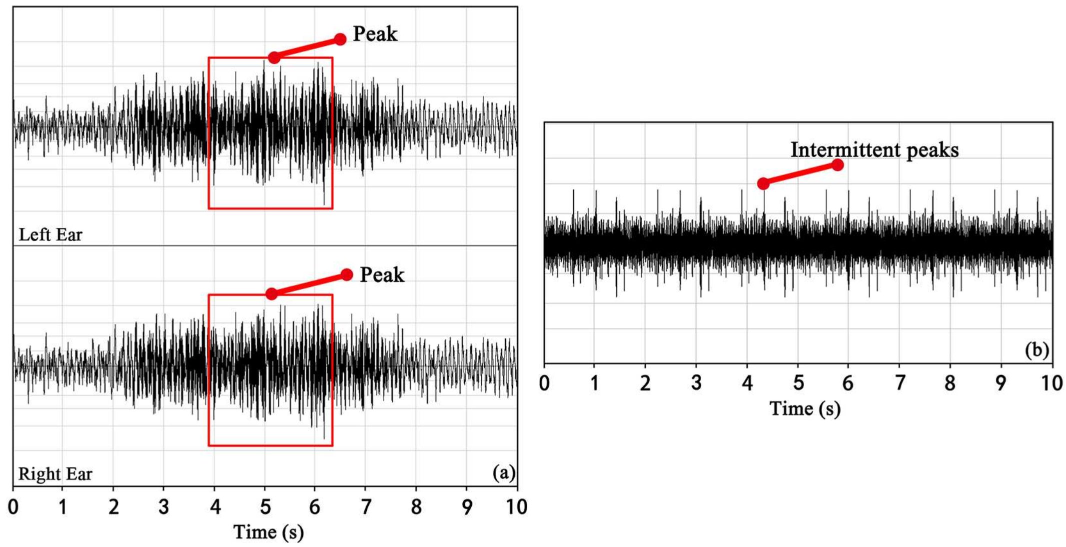

Figure 3. Normalized time signals of binaural metro sounds (a) and monaural fountain sound (b).

3 Results

3.1 Impact degree of factors influencing discomfort after mitigation

Wang et al. proposed that the discomfort caused by metro sound can be mitigated by adding the fountain sound [20]. However, they failed to identify the primary, secondary and significant influencing factors following the mitigation of discomfort. Consequently, it becomes difficult to propose the most effective measure to enhance the masking effect, or to suggest more targeted predictive factors for the masking effect. Therefore, in this section, a PLS model focused on the discomfort after mitigation was constructed to determine the influence degrees of different factors. Based on previous studies [32, 51–53], the potential factors influencing the levels of negative reactions encompassed both objective and subjective aspects. Objective factors related to various acoustic parameters, while subjective factors involved reactions such as subjective loudness and activity disturbance, as well as population characteristics like gender and noise sensitivity. Aligning with these prior studies, this section categorized the potential factors influencing the discomfort into objective and subjective groups. Regarding objective influencing factors, previous studies [6, 15, 16] proposed that the sound levels including L_{Aeq} of combined sound, L_{Aeq} of metro sound and L_{Aeq} of fountain sound, as well as the SNR, should be considered when exploring the objective influence mechanism of negative reactions to combined sound. Therefore, these objective influencing factors were selected for inclusion in the PLS model. As for the subjective influencing factors, based on the potential influences on reaction to noise, this study selected several population characteristics based on previous studies [51, 52, 54]: gender, personality, noise sensitivity, noise adaptability, noise preference, and noise loudness, which were investigated before conducting the auditory experiments. Correlation analyses were then conducted to examine the relationships between these data and the discomfort level. Since the collected multi-dimensional data on negative reactions (subjective loudness, discomfort, and memory disturbance) did not follow a typical normal distribution (a normality test with a significance level lower than 0.05), a nonparametric statistical method was employed. Specifically, Spearman's correlation analyses were used to assess the correlations. The results showed weak correlations between these population characteristics and the discomfort (Spearman's correlation coefficients below 0.14). Consequently, these population factors were excluded from the model. In terms of subjective reaction, among the negative reaction evaluation indices focused on in this study, the subjective loudness exhibited a strong correlation with the discomfort (Spearman's correlation coefficient approaching 0.8). Consequently, it was integrated into the PLS model for assessing the discomfort. Additionally, the memory disturbance showed a relatively strong correlation with the discomfort (Spearman's correlation coefficient higher than 0.3) and was thus also incorporated into the model.

As for model construction, after importing all the data, various potential influencing factors and the discomfort were incorporated into the model-building window. The discomfort was set as the dependent variable, while the potential influencing factors were designated as independent variables. Based on one previous study [33], the hypothetical paths of potential influences were established, and a PLS calculation was performed. Figure 4 presents the PLS prediction path model for the discomfort based on these potential influencing factors. To validate the reliability and validity of the model's prediction results, relevant indicators were extracted. The results revealed that both Cronbach's Alpha and AVE for the sound levels exceeded 0.8, and the Composite Reliability value for the sound levels was higher than 0.9. These coefficients significantly surpassed the standard thresholds

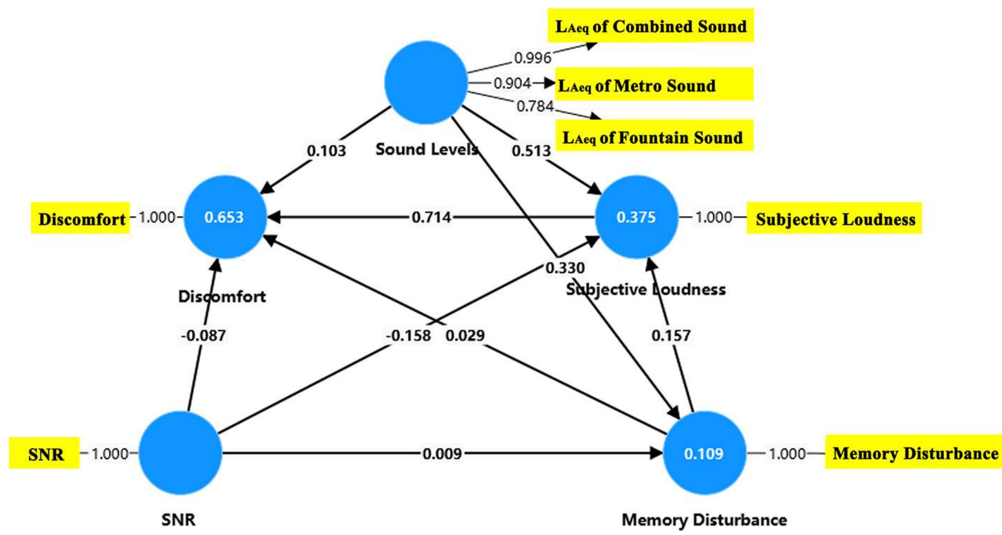

Figure 4. PLS path model for discomfort after mitigation.

(Cronbach's Alpha ≥ 0.65, Composite Reliability ≥ 0.7, and AVE ≥ 0.5) [45]. This demonstrates that the model exhibits strong reliability, consistency, and information interpretation capabilities, thus indicating the validity of the analytical results obtained from the discomfort PLS model.

In Figure 4, the number inside the blue circle represents fitting coefficient, a metric used to assess the predictive effect of model. A higher fitting coefficient indicates superior predictive capability. The fitting coefficient for the discomfort, indicated by the number inside the blue circle of discomfort, was 0.653, exceeding 0.5, which demonstrates that the predictive effect of the discomfort based on the aforementioned subjective and objective factors was relatively good. Table 2 demonstrates the test results on the total effect size of the aforementioned potential influencing factors on the discomfort. The larger the absolute value of total effect size, the more pronounced the influence of specific factor on target factor. According to the absolute value of total effect size, the subjective loudness was considered the most important factor influencing the discomfort. Next were the sound levels, and the SNR and memory disturbance followed. Regarding the breakdown of sound levels, the load coefficients for L_{Aeq} of combined sound, L_{Aeq} of metro sound, and L_{Aeq} of fountain sound were all close to or exceeded 0.8. This indicates that these parameters adequately reflected the influences of sound levels. Among these, L_{Aeq} of combined sound and L_{Aeq} of metro sound exhibited higher load coefficients, suggesting that they provided a better explanation of how the sound levels influenced the negative reactions including the discomfort, subjective loudness, and memory disturbance. Conversely, the load coefficient for L_{Aeq} of fountain sound was the lowest, indicating it's the weakest capability to explain these effects.

In Figure 4, the number positioned on the arrow signifies direct effect size, which evaluates the direct impact degree of a particular factor on a target factor and was partially listed in Table 2. The larger the absolute value of direct effect size, the more pronounced the direct influence of specific factor on target factor. When comparing the direct impact degrees of different influencing factors on the discomfort, according to the absolute value of direct effect size, listed in Table 2, the subjective loudness exerted the most significant direct impact, the direct impact of sound levels was ranked second, followed by the SNR and memory disturbance. This demonstrated that the analysis results for direct impact degree were similar to those for total impact degree.

Furthermore, a Bootstrap calculation was conducted on the discomfort model, yielding the significance test results regarding the influence of potential factors on the discomfort. These results are also listed in Table 2, presenting T Statistics values. A T Statistics value exceeding 2 indicates that the independent variable exerts a significant effect on a dependent variable, whereas a value below 2 suggests no significant impact. Among the potential influencing factors, the total T Statistics values for the sound levels, subjective loudness, memory disturbance, and SNR all exceeded 2, indicating that, given the total significance of the results, these four factors had significant influences on the discomfort.

According to the potential influencing paths, the impacts of different influencing factors, referred to as independent variables in the PLS model, encompassed both direct and indirect impacts on the discomfort. For example, the sound levels could directly influence the discomfort. Additionally, they can indirectly influence the discomfort by first influencing the subjective loudness or memory disturbance, and subsequently, the subjective loudness or memory disturbance influenced the discomfort. To uncover the main influence mechanisms, the impact degree of the direct influence path was firstly compared with that of the indirect influence path, which took into account the interaction effects between different

Table 2. Effect sizes and T Statistics values of potential influencing factors on discomfort.

	Direct effect size	Total effect size	Total T Statistics
Sound levels	0.103	0.517	27.898
Subjective loudness	0.714	0.714	44.081
Memory disturbance	0.029	0.141	5.974
SNR	−0.087	−0.199	11.133

influencing factors derived from the PLS model. These analyses were based on direct effect size and indirect effect size. Similar to the meaning of the direct effect size, the larger the absolute value of indirect effect size, the more pronounced the indirect influence. Based on these comparisons, the interdependence between the discomfort and its influencing factors, as well as the potential direct and indirect mechanisms influencing the discomfort, were defined. Given that the subjective loudness, sound levels, SNR and memory disturbance all emerged as the significant factors influencing the discomfort after mitigation, the focus of the aforementioned analyses was on these four significant influencing factors. Table 3 presents the effect sizes of direct and indirect influence paths of these significant influencing factors on the discomfort. Based on these, the specific analysis findings are as follows.

Regarding the interdependence, as well as the potential direct and indirect mechanisms, between the sound levels and the discomfort, as shown in Table 3, among all direct and indirect influence paths, the absolute value of effect size for the indirect influence path mediated by the subjective loudness – where the sound levels first influenced the subjective loudness and then the subjective loudness influenced the discomfort – was the highest. This means the indirect impact mediated by the subjective loudness was the most pronounced compared to the direct impact and other indirect impacts. Therefore, it is likely that the influence of sound levels on the discomfort was primarily mediated by the subjective loudness; specifically, the sound levels initially influenced the subjective loudness, which then the subjective loudness influenced the discomfort. Similar analysis results were found for the interdependence, as well as the potential direct and indirect mechanisms, between the SNR and the discomfort. In Table 3, among all direct and indirect influence paths, the absolute value of effect size for the indirect influence path mediated by the subjective loudness – where the SNR first influenced the subjective loudness and then the subjective loudness influenced the discomfort – was the highest. This demonstrated that the indirect impact mediated by the subjective loudness was the most pronounced compared to the direct impact and other indirect impacts. Therefore, it is likely that the influence of SNR on the discomfort was primarily mediated by the subjective loudness; specifically, the SNR initially influenced the subjective loudness, which then the subjective loudness influenced the discomfort.

Furthermore, regarding the interdependence, as well as the potential direct and indirect mechanisms, between the memory disturbance and the discomfort. As shown in Table 3, between the two direct and indirect influence paths, the absolute value of effect size for the indirect influence path mediated by the subjective loudness – where the memory disturbance first influenced the subjective loudness and then the subjective loudness influenced the discomfort – was higher than that for the direct influence path. This suggested that the indirect impact mediated by the subjective loudness was more pronounced compared to the direct influence. Accordingly, the impact of memory disturbance on the discomfort was primarily mediated by the subjective loudness. Specifically, the memory disturbance initially influenced the subjective loudness, which then the subjective loudness influenced the discomfort.

3.2 Impact degree of factors influencing memory disturbance after mitigation

Wang et al. suggested that adding the fountain sound can mitigate the memory disturbance induced by metro sound but were also unable to determine the primary, secondary and significant influencing factors for the memory disturbance after mitigation. To address this gap, the PLS model was employed to analyze the influence degrees of different factors on the memory disturbance after mitigation. The goal is to provide more effective insights for improving the masking effect and to propose more targeted predictive factors for such effect. When developing the PLS model for the memory disturbance, similar to the screening criteria for input independent variables in the PLS model related to the discomfort after mitigation, the objective influencing factors including L_{Aeq} of combined sound, L_{Aeq} of metro sound, L_{Aeq} of fountain sound, and the SNR were selected. Among the subjective factors that may influence the memory disturbance, population characteristics such as gender, personality, noise sensitivity, noise adaptability, noise preference, and noise loudness exhibited low correlations with the memory disturbance (Spearman's correlation coefficient below 0.07). Conversely, the subjective loudness demonstrated a relatively strong correlation with the memory disturbance (Spearman's correlation coefficient more than 0.3). Additionally, the discomfort also showed a relatively strong correlation with the memory disturbance (Spearman's correlation coefficient above 0.3). Therefore, the subjective loudness and discomfort were integrated into the PLS model for assessing the memory disturbance, while the population characteristic factors were excluded.

Table 3. The effect sizes of influence paths of significant influencing factors on discomfort.

Influence type	Influence path	Effect size
Direct influence	Sound levels → Discomfort	0.103
Indirect influence	Sound levels → Subjective loudness → Discomfort	0.367
Indirect influence	Sound levels → Memory disturbance → Discomfort	0.009
Indirect influence	Sound levels → Memory disturbance → Subjective loudness → Discomfort	0.037
Direct influence	SNR → Discomfort	−0.087
Indirect influence	SNR → Subjective loudness → Discomfort	−0.113
Indirect influence	SNR → Memory disturbance → Discomfort	0.000
Indirect influence	SNR → Memory disturbance → Subjective loudness → Discomfort	0.001
Direct influence	Memory disturbance → Discomfort	0.029
Indirect influence	Memory disturbance → Subjective loudness → Discomfort	0.112

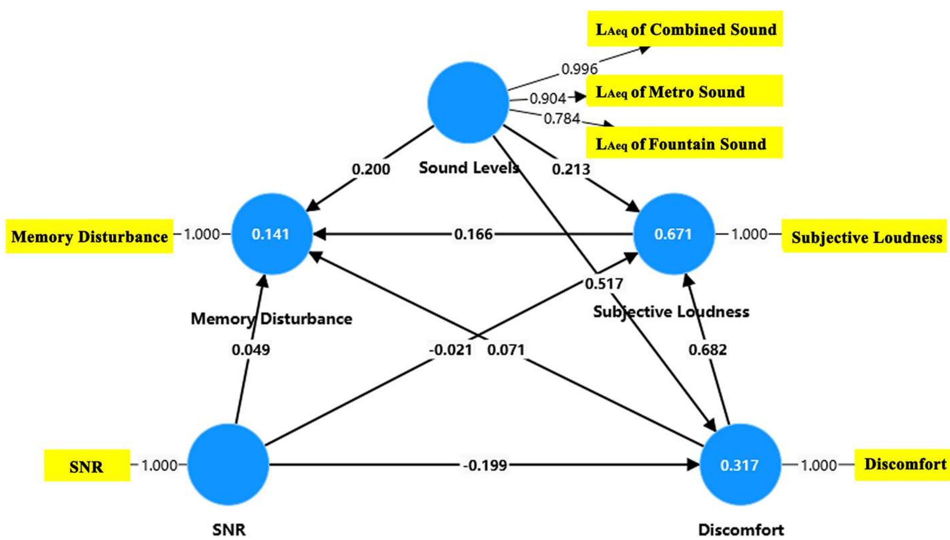

Figure 5. PLS path model for memory disturbance after mitigation.

In developing the PLS model for the memory disturbance, the potential influence paths of memory disturbance were set according to one previous study [33] and then the PLS calculation was conducted. Figure 5 depicts the PLS path model for the memory disturbance. Additionally, the relevant validation test indicators for the model were extracted. The results revealed that Cronbach's Alpha and AVE values for the sound levels exceeded 0.8, while the Composite Reliability value for the sound levels surpassed 0.9, significantly outperforming the PLS model's standard values. This signifies high reliability, strong consistency, and excellent explanatory power of the model. As a result, the findings from the output analysis of the memory disturbance PLS model should be highly credible.

In Figure 5, the fitting coefficient for the memory disturbance, indicated by the number inside the blue circle of memory disturbance, was lower than that for the discomfort based on the PLS model of discomfort. This indicates, based on the aforementioned subjective and objective factors, the predictive effect for the discomfort was better than that for the memory disturbance. Table 4 displays the test results on the total effect sizes of the aforementioned potential influencing factors on the memory disturbance. The absolute value of total effect size of the sound levels was the highest, followed by those for the subjective loudness and discomfort, while the absolute value of total effect size for SNR was significantly the lowest. This means considering total impact degree, the memory disturbance was predominantly influenced by the sound levels. The subjective loudness and discomfort were moderate influencing factors, whereas the SNR had the minimal impact on the memory disturbance.

When comparing the direct impact degrees of different influencing factors on the memory disturbance, based on the absolute values of direct effect sizes listed in Table 4, it was discovered that the sound levels exhibited the greatest direct impact, followed by the subjective loudness and discomfort, with the SNR having the weakest direct impact. A Bootstrap calculation was further conducted on the memory disturbance PLS model, and the total T Statistics values for the different influencing factors on the memory disturbance are also shown in Table 4. It can be seen that the total T Statistics values for the sound levels, discomfort and subjective loudness all exceeded 2, demonstrating their significant impacts on the memory disturbance. Conversely, the total T Statistics value for the SNR was below 2, indicating its relatively insignificant impact.

Table 4. Effect sizes and T Statistics values of potential influencing factors on memory disturbance.

	Direct effect size	Total effect size	Total T Statistics
Sound levels	0.200	0.330	13.831
Subjective loudness	0.166	0.166	3.655
Discomfort	0.071	0.184	6.010
SNR	0.049	0.009	0.375

Similar to the analysis method used for the discomfort PLS model, based on the absolute value of effect sizes of direct and indirect influence paths in the memory disturbance PLS model, this section first compared the impact degree of the direct influence path with those of the indirect influence paths. Accordingly, the interdependence between the memory disturbance and its influencing factors, as well as the potential direct and indirect mechanisms influencing the memory disturbance, were defined. Taking into account that the sound levels, subjective loudness and discomfort were the significant factors influencing the memory disturbance, while the impact of SNR was insignificant, the aforementioned analyses focused on these three significant influencing factors. Table 5 demonstrates the test results on the effect size of direct and indirect influence paths of these significant influencing factors on the memory disturbance. Regarding the interdependence, as well as the potential direct and indirect mechanisms, between the sound levels and the memory disturbance, among all direct and indirect influence paths, the absolute value of effect size for the direct influence path – where the sound levels directly influenced the memory disturbance – was the highest. This indicates the direct influence was stronger than all the indirect influences. Therefore, the impact of sound levels on the memory disturbance was primarily likely a direct effect, which was not mediated by the subjective loudness or the discomfort.

However, as for the interdependence, as well as the potential direct and indirect mechanisms, between the discomfort and the memory disturbance. Table 5 shows that between the two direct and indirect influence paths, the absolute value of effect size for the indirect influence path mediated by the subjective loudness – where the discomfort first influenced the subjective loudness and then the subjective loudness influenced the memory disturbance – was higher than that for the direct influence path. This means that the indirect impact mediated by the subjective loudness was the more pronounced compared to the direct influence. Therefore, it is likely that the impact of discomfort on the memory disturbance was primarily mediated through the subjective loudness, in particular, the discomfort first influenced the subjective loudness, which then the subjective loudness had a subsequent impact on the memory disturbance. Combined with the evaluation result of the mechanism by which the memory disturbance influenced the discomfort, as derived from the discomfort PLS model, it was found that the interaction between the memory disturbance and the discomfort was primarily mediated through the indirect impact of subjective loudness.

3.3 Prediction model for discomfort after mitigation

Previous studies proposed various methods for evaluating negative reactions to noise, including psychophysical model, perceptual model, artificial neural network model, decision tree model, etc. This study intended to initially select the previous proposed psychophysical model and perceptual model to predict negative reactions to combined sounds. A great number of psychoacoustic prediction models for combined sound effects were proposed to predict reaction level [13–17]. Following a previous study [6], three widely used psychoacoustic prediction models for combined sound effects, including the independent effects model, the energy summation model, and the energy difference model (summarized in Sect. 2.4), were selected to test their validity in predicting the levels of negative reactions in this study. Wang et al. [20] developed the prediction models for the discomfort after mitigation achieved by adding fountain sound to metro sound, based on these three models. However, they did not consider the significant factors that influenced the discomfort after mitigation, indicating a lack of scientific rigor in the development of those prediction models. Therefore, this section aimed to establish more scientifically rigorous prediction models for the discomfort after mitigation. This will be achieved by integrating the aforementioned three prediction models with the analysis results from Section 3.1, which identified the significant factors influencing the discomfort after mitigation.

Given that this study focused on the negative reaction to the combination of wanted and unwanted sounds (fountain sound and metro sound), rather than the combination of two unwanted sounds, following the previous studies [6, 19], the energy difference model was modified by removing the absolute value sign of the L_{Aeq} difference between the two sound sources. Combined the analysis results in Section 3.1, the independent variables used by these three psychoacoustic models – including L_{Aeq} of combined sound, L_{Aeq} of metro sound, and L_{Aeq} of fountain sound and SNR – were proven to significantly influence the discomfort. Therefore, this section firstly established the prediction models for the discomfort after mitigation based on these three combined sound reaction prediction models.

Table 5. The effect sizes of influence paths of significant influencing factors on memory disturbance.

Influence type	Influence path	Effect size
Direct influence	Sound levels → Memory disturbance	0.200
Indirect influence	Sound levels → Subjective loudness → Memory disturbance	0.035
Indirect influence	Sound levels → Discomfort → Memory disturbance	0.036
Indirect influence	Sound levels → Discomfort → Subjective loudness → Memory disturbance	0.058
Direct influence	Discomfort → Memory disturbance	0.071
Indirect influence	Discomfort → Subjective loudness → Memory disturbance	0.113

In terms of predicting the level of negative reaction caused by noise, previous studies have proposed two main methods: directly predicting reaction level and predicting mean reaction level. Both methods were proven to yield good evaluation effects [5]. However, the three combined sound reaction prediction models exhibited relatively low R^2 values (ranging from 0.25 to 0.35) in predicting the discomfort level. With the goal of developing the prediction models with high R^2 values to more effectively analyze the mechanism following discomfort mitigation, this section aimed to evaluate the mean discomfort level using the aforementioned three combined sound reaction prediction models. Specifically, the mean discomfort levels were calculated for each combined sound sample across 79 subjects. Then, through linear regression analysis, acoustic parameters were correlated with the mean discomfort levels to derive prediction models. Table 6 presents the prediction models for the mean discomfort level, which are based on the three combined sound reaction prediction models. The R^2 values for all models were close to or exceed 0.8, indicating strong predictive performance. Additionally, in order to offer a more comprehensive evaluation of the mechanism following discomfort mitigation, Table 6 also includes a prediction model for the mean discomfort level based solely on binaural L_{Aeq} of metro sound without the addition of fountain sound, as determined from previous statistical data [54].

As shown in Table 6, when predicting the mean discomfort level after mitigation due to the addition of fountain sound, the R^2 values of the independent effects model and the modified energy difference model were similar and higher than that of the energy summation model. This indicates that the independent effects model and the modified energy difference model outperformed the energy summation model in assessing the mean discomfort level. Since the R^2 values of the three prediction models were close to or above 0.8, the analysis outcomes derived from all three models were considered valid for further discussions. In all models, the coefficients for L_{Aeq} of combined sound, L_{Aeq} of metro sound, and L_{Aeq} of fountain sound were positive, signifying that rises in the sound levels correlated with increase in the discomfort level. In the independent effects model, the coefficient for L_{Aeq} of metro sound (0.092) exceeded the coefficient for L_{Aeq} of fountain sound (0.008). Based on the ratio of these coefficients, to attain a masking effect that aligns with the original scenario, if metro sound decreased by 1 dBA, fountain sound was able to increase around 11.5 dBA (calculated as 0.092/0.008). This further proves that, within an environment with the same L_{Aeq}, the discomfort elicited by single metro sound was more pronounced than when fountain sound was added to it. In the energy summation model, the coefficient for L_{Aeq} of combined sound (0.101) was lower than the coefficient for L_{Aeq} of metro sound (0.142) in the model without fountain sound. This suggests that as L_{Aeq} increased, the improvement in discomfort level became more significant. Analysis of the modified energy difference model revealed that introducing SNR on the basis of the energy summation model, which is based on global L_{Aeq}, can increase the R^2 value by almost 19%. This demonstrates that SNR is a crucial factor that should not be overlooked when predicting the mean discomfort level based on the total energy of combined sound.

Wang et al. examined how the SNR influenced the mean discomfort level after mitigation [20]. Specifically, they found that when binaural L_{Aeq} of combined sound reached 60 or 65 dBA, and the SNR exceeded −3 dBA but did not exceed 6 dBA, the mean discomfort level tended to decrease. In other cases, the mean discomfort level remained relatively stable as SNR changed. To quantify this effect, this study incorporated a Threshold factor related to SNR into the prediction models for the mean discomfort level. Specifically, when the conditions for decreasing the mean discomfort level were met, Threshold was set to 1; otherwise, it was set to 0. To prevent multicollinearity, this Threshold factor was excluded from the modified energy difference model. The refined energy summation model and the refined independent effects model, which incorporated the Threshold factor, are also presented in Table 6. In such refined models, the coefficients of Threshold were negative, indicating the decreases in mean discomfort level under the specified conditions. After incorporating the Threshold, the R^2 value of the energy summation model increased by about 19%, similar to the increase observed when SNR was included to the energy summation model. This suggests that Threshold and SNR had comparable effects on correcting the energy summation model. Meanwhile, the R^2 value of the independent effects model showed an increase of about 3% after adding Threshold. Although the increase was relatively small, the refined independent effects model exhibited the best prediction effect (the highest R^2 value) among the acoustic parameter-based prediction models.

Table 6. Prediction models for mean discomfort level after mitigation.

Situation	Model form	Prediction model	R^2
No fountain sound added	No	$\mathrm{MD_cL}=0.142L_{\mathrm{SM}}-5.287$	0.993
With fountain sound added	Independent effects model	$\mathrm{MD_cL}=0.092L_{\mathrm{SM}}+0.008L_{\mathrm{FS}}-3.505$	0.906
With fountain sound added	Energy summation model	$\mathrm{MD_cL}=0.101L_{\mathrm{T}}-3.911$	0.770
With fountain sound added	Modified energy difference model	$\mathrm{MD_cL}=0.101L_{\mathrm{T}}-0.035\mathrm{SNR}-3.963$	0.916
With fountain sound added	Refined independent effects model	$\mathrm{MD_cL}=0.085L_{\mathrm{SM}}+0.027L_{\mathrm{FS}}-0.245\mathrm{T}-4.084$	0.932
With fountain sound added	Refined energy summation model	$\mathrm{MD_cL}=0.122L_{\mathrm{T}}-0.424\mathrm{T}-5.042$	0.918
With fountain sound added	Perceptual model	$\mathrm{MD_cL}=0.912\mathrm{MS_LL}-0.058$	0.978
With fountain sound added	Perceptual model	$\mathrm{MD_cL}=1.294\mathrm{MLMD}-0.890$	0.741

Notes. $\mathrm{MD_cL}$: Mean discomfort level; L_{SM}: Binaural L_{Aeq} of metro sound; L_{FS}: Binaural L_{Aeq} of fountain sound; L_{T}: Binaural L_{Aeq} of combined sound; T: Threshold, 1 when SNR exceeds −3 dBA but is no greater than 6 dBA, and global L_{Aeq} levels are between 60 and 65 dBA, otherwise 0; $\mathrm{MS_LL}$: Mean subjective loudness level; MLMD: Mean level of memory disturbance; R^2: Coefficient of determination.

In addition to the psychophysical models based on acoustic parameters, previous studies introduced a method for constructing perceptual models that utilize a specific reaction level to predict another specific reaction level [15, 16]. Drawing from the findings presented in Section 3.1, which revealed that both the subjective loudness and memory disturbance significantly influenced the discomfort, this study devised a model to predict the mean discomfort level based independently on the mean subjective loudness level and the mean level of memory disturbance, as outlined in Table 6. Similar to the calculation method of the mean discomfort level, the mean subjective loudness level was calculated the mean value of subjective loudness level across all 79 participants for each combined sound sample, and similarly, the mean level of memory disturbance was also calculated in the same manner. Compared to other prediction models that relied on the acoustic parameters, the model based on the mean subjective loudness level achieved the highest prediction accuracy, with an R^2 value approaching 0.98. However, the model based on the mean level of memory disturbance yielded the weakest prediction effect, with an R^2 value close to 0.75.

3.4 Prediction model for memory disturbance after mitigation

Based on the three psychophysical prediction models for combined sound reaction selected in this study (summarized in Sect. 2.4), as well as the analyses of significant influencing factors of memory disturbance after mitigation achieved by incorporating the fountain sound (discussed in Sect. 3.2), this section proposed a series of prediction models specifically aimed at determining the level of memory disturbance after mitigation. Specifically, according to the findings presented in Section 3.2, the objective significant factors influencing the memory disturbance were identified as L_{Aeq} of combined sound, L_{Aeq} of metro sound, and L_{Aeq} of fountain sound. These factors served as the independent variables for the energy summation model and the independent effects model. The SNR, on the other hand, was deemed non-significant. Since the energy difference model incorporates the non-significant factor SNR based on the energy summation model, this section chose to exclude it and instead constructed the prediction models for the memory disturbance level solely based on the independent effects model and the energy summation model.

Similar to the prediction result for the discomfort level, the predictions for memory disturbance level using the independent effects model and the energy summation model yielded low R^2 values of around 0.11. In order to obtain more effective evaluation results of the mechanism following memory disturbance mitigation using prediction models with high R^2 values, this section focused on establishing the prediction models for the mean level of memory disturbance. Specifically, for each combined sound sample, the mean memory disturbance level across 79 subjects was calculated. Subsequently, the sound levels were linearly fitted to the mean levels of memory disturbance to derive the prediction models, as presented in Table 7. The R^2 values of these prediction models were close to 0.9, indicating their high predictive effectiveness. Additionally, to provide a more comprehensive reference for analyzing the mechanism following memory disturbance mitigation, Table 7 also includes a prediction model for the mean level of memory disturbance based on binaural L_{Aeq} of metro sound without the addition of fountain sound, derived from previous statistical data [22].

As shown in Table 7, the R^2 values of the independent effects model and the energy summation model in predicting the mean level of memory disturbance were very close, demonstrating comparable predictive accuracy for both models. In both models, the coefficients for L_{Aeq} of combined sound, L_{Aeq} of metro sound, and L_{Aeq} of fountain sound were all positive, suggesting that as the sound levels increased, the level of memory disturbance also increased. In the independent effects model, the coefficient for L_{Aeq} of fountain sound (0.029) was

Table 7. Prediction models for mean level of memory disturbance after mitigation.

Situation	Model form	Prediction model	R^2
No fountain sound added	No	MLMD=$0.065L_{\mathrm{SM}}-1.402$	0.944
With fountain sound added	Independent effects model	MLMD=$0.042L_{\mathrm{SM}}+0.029L_{\mathrm{FS}}-1.679$	0.887
With fountain sound added	Energy summation model	MLMD=$0.072L_{\mathrm{T}}-1.969$	0.883
With fountain sound added	Perceptual model	MLMD=$0.552\mathrm{MS_LL}+1.012$	0.809
With fountain sound added	Perceptual model	MLMD=$0.573\mathrm{MD_cL}+1.116$	0.741

Notes. MLMD: Mean level of memory disturbance; L_{SM}: Binaural L_{Aeq} of metro sound; L_{FS}: Binaural L_{Aeq} of fountain sound; L_{T}: Binaural L_{Aeq} of combined sound; $\mathrm{MS_LL}$: Mean subjective loudness level; $\mathrm{MD_cL}$: Mean discomfort level; R^2: Coefficient of determination.

lower than that of the L_{Aeq} of metro sound (0.042). Based on the ratio of these coefficients, to attain a masking effect that aligns with the original scenario, if metro sound decreased by 1 dBA, fountain sound was able to increase around approximately 1.4 dBA (calculated as 0.042/0.029). This further proves that, within an environment with the same L_{Aeq}, the memory disturbance elicited by single metro sound was more pronounced than when fountain sound was added to it. This increase value (1.4 dBA) was lower than the 11.5 dBA increase in fountain sound mentioned in the discomfort mitigation. In the energy summation model, the coefficient for L_{Aeq} of combined sound (0.072) was higher than the coefficient for L_{Aeq} of metro sound (0.065) in the model without the addition of fountain sound. This indicates that as L_{Aeq} increased, the improvement effect on the memory disturbance gradually weakened.

Apart from objective factors such as the sound levels, among subjective factors, it was proven that both the subjective loudness and discomfort significantly influenced the memory disturbance. Based on the theory of perceptual prediction model, the prediction models for the mean level of memory disturbance were further constructed by separately utilizing the mean subjective loudness level and mean discomfort level, as shown in Table 7. These models demonstrated good prediction accuracy, with an R^2 value exceeding 0.7. Nevertheless, in comparison to the prediction models based solely on the sound levels, the R^2 values of these models were relatively lower. Between the two models that based on subjective factors, the R^2 value of model based on the mean subjective loudness level was slightly higher than that based on the mean discomfort level.

4 Discussions and conclusions

Firstly, this study proposed that the discomfort after mitigation and memory disturbance after mitigation, achieved by incorporating fountain sound into structure borne sound from a metro, showed somewhat different influencing mechanisms. Specifically, considering the total impact degree, the discomfort after mitigation was predominantly influenced by the subjective loudness, followed by the sound levels, then the SNR and the memory disturbance. Regarding the memory disturbance after mitigation, the sound levels were the most important influencing factor, the next was the discomfort and subjective loudness, and the influence of SNR was relatively the weakest. This could be interpreted as follows: the experience of discomfort was likely to involve a conscious processing of perception input, where the subjective loudness of combined sound sample was first assessed, followed by a determination of the corresponding level of discomfort. However, the judgment of memory disturbance of combined sound sample often seemed to bypass such a pronounced stage of conscious processing, where memory disturbance was directly defined according to sound levels. Moreover, considering the total significant test result, all the subjective and objective factors selected in this study – including the sound levels, subjective loudness, SNR, and discomfort – emerged as significant factors influencing the discomfort. While only the sound levels, subjective loudness, and discomfort were identified as significant factors influencing the memory disturbance, the SNR exhibited a non-significant impact. Furthermore, in terms of the discomfort, the impacts of sound levels or SNR on it was primarily that the sound levels or SNR influenced the subjective loudness first, which subsequently influenced the discomfort. However, as for the memory disturbance, the impact of sound levels on it appeared to be primarily direct, bypassing the indirect influence via the subjective loudness or discomfort. The interaction influence between the memory disturbance and the discomfort was primarily mediated through the subjective loudness, that is, one of the two factors first influenced the subjective loudness, which subsequently exerted an influence on the other factor.

Secondly, this study proposed that the discomfort after mitigation and memory disturbance after mitigation, achieved by incorporating fountain sound into structure borne sound from a metro, showed somewhat different prediction mechanisms. In predicting the mean discomfort level after mitigation, among the models based on acoustic parameters, the independent effects model and the modified energy difference model performed better than the energy summation model. When taking into account the significant influence of SNR and introducing a related quantitative correction factor, Threshold, into both the independent effects model and the energy summation model, the refined independent effects model yielded the highest prediction accuracy, and the prediction accuracy of the refined energy summation model became comparable to that of the modified energy difference model. However, when it comes to predicting the mean disturbance level of memory after mitigation, among the prediction models utilizing acoustic parameters, the independent effects model and the energy summation model were basically equally effective in the prediction, and considering the insignificant impact of SNR on the memory disturbance, there was no need to employ the energy difference model, which introduces a correction factor SNR based on the energy summation model, for such a prediction. In addition, in predicting the mean discomfort level after mitigation, compared to psychophysical prediction models relying solely on acoustic parameters, the perceptual prediction model based on the mean subjective loudness level exhibited the highest effectiveness, and the perceptual prediction model based on the mean comfort level exhibited the weakest effectiveness. However, when it comes to predicting the mean disturbance level of memory after mitigation, the methods relying on acoustic parameters (psychophysical model) were proven to be more effective than those based on subjective reactions (perceptual model), which included the mean subjective loudness level and mean discomfort level.

Thirdly, this study proved that the addition of fountain sound had the ability to mitigate the memory disturbance caused by structure borne sound from a metro under three global L_{Aeq} levels: 55, 60, and 65 dBA, as the SNR changed from −9 to 6 dBA. This finding is consistent with a previous analysis that specifically examined a SNR of 0 dBA under the same global L_{Aeq} environments [22]. Moreover, both this study and a previous study [20] suggest that incorporating fountain sound can mitigate the discomfort caused by structure borne sound from a metro, and the analytical method employed in this study was more scientific given that it took into account the significant factors influencing the discomfort after mitigation. Furthermore, fountain sound, as a higher frequency sound, is effective as a masking agent potentially because it creates a distracting effect that diverts attention from the lower frequency sound of structure borne sound from a metro. Consequently, as fountain sound is introduced and people become aware of and enjoy the pleasant fountain sound, their discomfort and memory disturbance caused by original structure borne sound from a metro tend to diminish.

This study also proposed that the optimization mechanisms for discomfort and memory disturbance differed after the introduction of fountain sound. As global L_{Aeq} level increased from 55 to 65 dBA, the mitigation effect on the discomfort became more significant, whereas the mitigation effect on the memory disturbance gradually diminished. Furthermore, to attain a masking effect that aligns with the original scenario, if structure borne sound from a metro reduced by 1 dBA, the L_{Aeq} increased by fountain sound in terms of the memory disturbance was lower than the L_{Aeq} increased by fountain sound in terms of the discomfort.

This study still possesses certain limitations, and on this basis, there is room for further exploration. Firstly, this study conducted the fountain sound masking experiments using the combined sound samples created by adjusting and combining one sample of metro sound with one sample of fountain sound. The selection of these individual samples was based on their representativeness: specifically, the sample of metro sound was collected in a high-rise commercial office building with a framed structure, located adjacent to one trunk line of the Guangzhou Metro. The specific sound sample collection site, located on the bottom floor of investigated commercial office building and adjacent to some commercial areas such as a café, was a relatively enclosed cubic space measuring approximately 4 m in length, 5 m in width, and 4 m in height. Considering the similarity in train type and operating speed on metro trunk lines, which results in comparable vibration sources, and the increasing number of high-rise commercial office buildings with frame structure being constructed near these lines, along with the fact that such a dimension of sound sample collection space is quite common on the bottom floors of commercial office buildings, the typicality of the metro line, building structure, and building space is likely to generate typical metro sound. As for water sound, fountain sound is a representative water body in the domain of water classification [26], the chosen fountain sound sample exhibits the typical characteristic of fountain [55], which is the water that ejects from ground.

Considering the potential influence of acoustic characteristics, such as the shape of the frequency spectrum curve, on noise reactions [56–59], it is imperative to introduce typical samples of metro sound and fountain sound with significantly different acoustic characteristics for further research. This may assist in incorporating factors like spectral property as corrections into the PLS models and prediction models, thus enhancing the universality and applicability of the influence and prediction mechanisms derived from these models. Furthermore, if corrections are needed, the degree of change in the model's results depends on the magnitude of the correction factor. If the characteristics of the sounds strongly deviate from the predefined ones, the magnitude of the correction factor could be large, this may render the originally established models and results less valid and necessitate significant corrections to the original models and results. Specifically, the significant factors influencing the discomfort and memory disturbance after mitigation might shift. Upon integrating these revised significant influencing factors into the prediction models, the models themself may undergo alterations. Consequently, based on these revised models, both the potential optimization of discomfort and memory disturbance after fountain sound introduction, as well as its underlying influence and prediction mechanisms, would necessitate redefinition.

Secondly, before the auditory experiments, a series of metro sound samples were collected from some high-rise commercial office buildings along metro trunk lines, which are commonly influenced by such noise. The findings reveal that, in most instances, the exposure level of metro sound typically fell between 50 and 65 dBA [54]. Drawing from a previous study [6], three higher levels of metro sound (55, 60, and 65 dBA) were chosen as global L_{Aeq}. This implies that the evaluation results corresponded to global L_{Aeq} levels ranging from 55 to 65 dBA. However, there are situations where L_{Aeq} level of metro sound could be low, for example, lower than 55 dBA, and could also be higher, particularly in areas close to metro lines. Therefore, further investigation remains essential into the masking mechanism of metro sound, specifically examining the impacts of introducing fountain sound at global L_{Aeq} level both below 55 dBA and above 65 dBA.

Thirdly, one relevant study [22] found that, among the learning activities such as calculation, judgement, and memory, memory activity was the most disrupted by metro sound from 50 to 65 dBA. This means that among the three learning activities, the optimization of memory activity proved to be the most necessary, accordingly, this study focused on the memory activity. This study discovered that adding fountain sound reduced the memory disturbance caused by metro sound, indicating that compared to metro sound, the additional fountain sound led to a less significant impact on the memory performance. However, it is important to note that this result is limited to memory activity. Previous studies suggested that the type of activity being evaluated can affect the influence mechanism of activity disturbance [22, 35, 60], implying that it may also affect the masking mechanism of activity disturbance. Therefore, there remains a need to explore the masking mechanism of fountain sound on disturbances caused by metro sound during other types of learning activities, including listening tests and reading comprehension, among others. For other types of activities, in some cases, the introduction of fountain sound could potentially amplify the disturbance level of a particular activity caused by metro sound, in such scenarios, compared to metro sound, fountain sound contributes to a more pronounced significant impact on the activity performance. In other cases, it could corroborate the result from this study, that incorporating fountain sound can mitigate the disturbance level for a specific activity caused by metro sound. However, in these two cases, the underlying influence and prediction mechanisms could differ from those in this study.

Finally, apart from psychophysical model and perceptual model used in this study, previous studies proposed several methods for constructing noise reaction model, such as artificial neural network model, decision tree model, vector autoregression model, etc. Future research should further test the effectiveness of the aforementioned models in predicting the masking effects of this study. Additionally, the linear models established in this study represent an initial attempt based on proposed models, and future research could build on this by incorporating the observed interactions into the linear models as interaction terms, in order to reflect the influence of the interactions between independent variables on the dependent variable and increase the accuracy of model predictions.

The conclusions of this study have wide impacts, covering both practical applications and academic insights. Firstly, considering that apart from the sound levels, the subjective loudness was another main influencing factor of the discomfort after mitigation and memory disturbance after mitigation, which was achieved by adding fountain sound to metro sound. In order to improve the mitigation effects, in addition to controlling sound exposure level, reducing people's perception of subjective loudness level due to the combination of metro sound and fountain sound is also crucial. To accomplish this, a series of strategies can be implemented to reduce the perceived subjective loudness level due to metro sound and fountain sound. These strategies include encouraging residents in nearby areas to use metro as their daily transportation, actively promoting government policies that aim to mitigate the negative impact of metro noise and enhance the beneficial effects of fountain sound, increasing the deployment of fountain sound in outdoor spaces, and fostering public involvement in the planning and design of metro system and fountain system [61]. Although these measures cannot directly alter the physical level of metro sound and fountain sound, they can effectively reduce people's perceived level of subjective loudness resulting from the two types of sounds, thus optimizing the masking effects. This suggests that considerable research and practical engineering efforts can be sequentially undertaken to test the actual effects of these proposed measures, ultimately leading to the minimization of adverse effects of metro sound on population.

Secondly, it was found that the discomfort and memory disturbance, after mitigation by incorporating fountain sound into metro sound, had somewhat different influence mechanisms. Considering that the subjective loudness was the most important determinant of the discomfort, the secondary significant influencing factor, namely the sound levels, appeared to exert their influence on the discomfort primarily in an indirect manner, through their first impact on the subjective loudness and then the subjective loudness influenced the discomfort. Therefore, the optimal strategy to enhance the optimization effect for the discomfort was to decrease the subjective loudness level. However, taking into account that the sound levels were the principal factor influencing the memory disturbance, and that their impact to the memory disturbance appeared to be primarily direct, bypassing the intermediary influence through the subjective loudness or discomfort, the most effective strategy to enhance the masking effect for the memory disturbance was to reduce the sound levels of both sound sources. This suggests that different optimization goals necessitate correspondingly different optimization measures. In an area where specific learning activities are not required, such as the rest area of a dental clinic surrounded by dental offices, when the aforementioned measures to decrease the subjective loudness level are effectively implemented, the masking effect of discomfort would experience enhancement. Conversely, in the office setting primarily dedicated to memory task, implementing strategies such as vibration reduction are suggested to decrease the sound level of metro sound. The implementation of these strategies can effectively help to create a more comfortable office building environment. Furthermore, apart from the aforementioned optimal strategies, the results of this study also indicate that while the incorporation of fountain sound can potentially alleviate various negative reactions due to metro sound, the optimal masking strategy may vary depending on the type of reaction. Therefore, further extensive studies are warranted to elucidate the distinction in optimal masking strategy for different types of reactions.

Finally, it was found that the discomfort and memory disturbance, after mitigation by incorporating fountain sound into metro sound, had somewhat different prediction mechanisms. In the case of discomfort after mitigation, the most effective prediction method for it relied on the subjective loudness level. This means when it is necessary to predict the discomfort level, it is imperative to conduct investigation to ascertain the subjective loudness level perceived by population due to metro sound masked with fountain sound, and subsequently use this finding to predict the discomfort level. Conversely, for predicting the memory disturbance after mitigation, the most effective method was to use the sound levels, this indicates when it is necessary to predict the memory disturbance level, it is prudent to adopt measurement or simulation method to obtain the sound level of metro sound within indoor space, and then integrate this data with the playback sound level of indoor fountain sound. Subsequently, these data can be used to predict the memory disturbance level. The implementation of these strategies can help effectively predict the masking effects of negative reactions within office building environment. Furthermore, apart from the aforementioned optimal prediction methods, this finding underscores that different prediction targets may require distinct optimal prediction methods for assessing the masking effect. Consequently, further extensive studies are needed to clarify the differences in the optimal prediction method for assessing masking effects across various types of reactions.

Acknowledgments

This work was supported by the School of Architecture of South China University of Technology, which permitted the team to conduct this research. The authors would also like to thank all the subjects in the auditory experiments.

Funding

This work was supported by the Scientific Research Foundation Project at Fujian University of Technology [grant number GY-Z24011].

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to this article.

Data availability statement

Data are available on request from the authors.

References

1. American National Standards Institute: Definitions, 2020.
2. A.L. Brown: Soundscapes and environmental noise management. Noise Control Engineering Journal 58 (2010) 493–500.
3. American National Standards Institute: Acoustical Terminology. New York, 2013.
4. J. Kang, B. Schulte-Fortkamp: Soundscape and the Built Environment. CRC Press, Boca Raton, FL, USA, 2016.
5. J.G. Walker, M.F.K. Chan: Human response to structurally radiated noise due to underground railway operations. Journal of Sound and Vibration 193 (1996) 49–63.
6. T.M. Leung, C.K. Chau, S.K. Tang, J.M. Xu: Developing a multivariate model for predicting the noise annoyance responses due to combined water sound and road traffic noise exposure. Applied Acoustics 127 (2017) 284–291.
7. B.D. Coensel, S. Vanwetswinkel, D. Botteldooren: Effects of natural sounds on the reaction of road traffic noise. The Journal of the Acoustical Society of America 129 (2011) 148–153.
8. M. Rådsten-Ekman, Ö. Axelsson, M.E. Nilsson: Effects of sounds from water on reaction of acoustic environments dominated by road-traffic noise. Acta Acustica United with Acustica 99 (2013) 218–225.
9. J.Y. Hong, Z.T. Ong, B. Lam, K. Ooi, W.S. Gan, J. Kang, J. Feng, S.-T. Tan: Effects of adding natural sounds to urban noises on the perceived loudness of noise and soundscape quality. Science of the Total Environment 711 (2020) 134571.
10. M.E. Nilsson, J. Alvarsson, M. Rådsten-Ekman, K. Bolin: Auditory masking of wanted and unwanted sounds in a city park. Noise Control Engineering Journal 58 (2010) 524–531.
11. M.E. Nilsson, J. Alvarsson, M. Rådsten-Ekman, K. Bolin: Loudness of fountain and road traffic sounds in a city park, in: 16th International Congress on Sound and Vibration 2009, ICSV, 2009.
12. Ö. Axelsson, M.E. Nilsson, B. Hellström, P. Lundén: A field experiment on the impact of sounds from a jet-and-basin fountain on soundscape quality in an urban park. Landscape and Urban Planning 123 (2014) 49–60.
13. S.M. Taylor: A comparison of models to predict annoyance reactions to noise from mixed sources. Journal of Sound and Vibration 81 (1982) 123–138.
14. J.B. Ollerhead: Predicting public reaction to noise from mixed sources, in: Proceedings – International Conference on Noise Control Engineering, 1978.
15. C. Marquis-Favre, L.A. Gille, L. Breton: Combined road traffic, railway and aircraft noise sources: total noise annoyance model appraisal from field data. Applied Acoustics 180 (2021) 108127.
16. M. Pierrette, C. Marquis-Favre, J. Morel, L. Rioux, M. Vallet, S. Viollon, A. Moch: Noise annoyance from industrial and road traffic combined noises: a survey and a total annoyance model comparison. Journal of Environmental Psychology 32 (2012) 178–186.
17. C.G. Rice, K. Izumi: Annoyance due to combinations of noises, in: Proceedings – International Acoustic Speech Conference, 1984, pp. 287–294.
18. J.Y. Jeon, J.K. Ryu, P.J. Lee: A quantification model of overall dissatisfaction with indoor noise environment in residential buildings. Applied Acoustics 71 (2010) 914–921.

19. T.L. Nguyen, H.Q. Nguyen, T. Yano, T. Nishimura, T. Sato, T. Morihara, Y. Hashimoto: Comparison of models to predict annoyance from combined noise in Ho Chi Minh City and Hanoi. Applied Acoustics 73 (2012) 952–959.
20. Q. Wang, W. Hongwei, W. Xiong, C. Yang: Developing multivariate models for predicting the level of dissatisfaction due to a specific metro noise masked with four specific water sounds. Applied Acoustics 200 (2022) 109082.
21. Q. Wang, W. Hongwei, Y. Zhang, N. Zou: Evaluating the mitigating effects of water sounds on multi-dimensional negative reactions due to secondary radiation noise. Acta Acustica United with Acustica 8 (2024) 1–22.
22. Q. Wang, W. Hongwei, Y. Zhang, N. Zou, Z. Huang: Metro noise-induced activity disturbances and their water sound-based countermeasures. Noise Control Engineering Journal 72 (2024) 210–227.
23. P. Zahorik: Assessing auditory distance perception using virtual acoustics. The Journal of the Acoustical Society of America 111 (2002) 1832–1846.
24. S. Pujol: Le bruit environnemental en milieu urbain: exposition d'une population d'enfants et performances scolaires. Doctoral thesis, University of Franche-Comté, 2012.
25. Q. Tenailleau: Multi-exposition en milieu urbain: approche multi-echelle del'exposition humaine au bruit et à la pollution atmosphérique. Doctoral thesis, University of Franche-Comté, 2014.
26. S. Dewar: Water features in public places – human responses. Graduate Diploma in Landscape and Architecture thesis, Queensland University of Technology, Queensland, Australia, 1990, pp. 104–143.
27. https://www.findsounds.com/ [accessed 22 November 2021].
28. S. Torresin, R. Albatici, F. Aletta, F. Babich, T. Oberman, S. Siboni: Indoor soundscape assessment: a principal components model of acoustic perception in residential buildings. Building and Environment 182 (2020) 107152.
29. International organization for standardization (ISO): ISO/TS 12913-3:2019, Acoustics Soundscape – Part 3: Data analysis. Geneva, Switzerland, 2019.
30. M. Yang, M. Masullo: Combining binaural psychoacoustic characteristics for emotional evaluations of acoustic environments. Applied Acoustics 210 (2023) 109433.
31. B. Berglund, T. Lindvall, D.H. Schwela: Guidelines of Community Noise. World Health Organization, 1999.
32. M. Zhang, J. Kang: Subjective evaluation of urban environment: a case study in Beijing. International Journal of Environment and Pollution 39 (2009) 187–199.
33. K.C. Lam, P.K. Chan, T.C. Chan, W.H. Au, W.C. Hui: Annoyance response to mixed transportation noise in Hong Kong. Applied Acoustics 70 (2009) 1–10.
34. T. Nowakowski, P. Komorski: Tram noise annoyance: the role of different psychoacoustic measures in the assessment of noise. Applied Acoustics 219 (2024) 109946.
35. D. Li, Y. Huang: The discomfort model of the micro commercial vehicles interior noise based on the sound quality analyses. Applied Acoustics 132 (2018) 223–231.
36. H. Ma, T. Yano: An experiment on auditory and non-auditory disturbances caused by railway and road traffic noises in outdoor conditions. Journal of Sound and Vibration 277 (2004) 501–509.
37. M.L. Cantuaria, F.B. Waldorff, L. Wermuth, E.R. Pedersen, A.H. Poulsen, J.D. Thacher, O. Raaschou-Nielsen, M. Ketzel, J. Khan, V.H. Valencia, J.H. Schmidt: Residential exposure to transportation noise in Denmark and incidence of dementia: national cohort study. BMJ-British Medical Journal 374 (2021) n1954.
38. Y. Zhang, D. Ou, Q. Chen, S.X. Kang, G.H. Qu: The effects of indoor plants and traffic noise on English reading comprehension of Chinese university students in home offices. Frontiers in Psychology 13 (2022) 1003268.
39. J.M. Fields, R.G. De Jong, T. Gjestland, I.H. Flindell, R.F.S. Job, S. Kurra, P. Lercher, M. Vallet, T. Yano, R.T.A.R. UNIVERSITY, R. Guski: Standardized general-purpose noise reaction questions for community noise surveys: research and a recommendation. Journal of Sound and Vibration 242 (2001) 641–679.
40. J. Kim, S. Lee, S. Kim, H. Song, J. Ryu: Quantitative study on the influence of non-acoustic factors on annoyance due to floor impact noise in apartments. Applied Acoustics 202 (2023) 109144.
41. H.M.E. Miedema, H. Vos: Noise annoyance from stationary sources: relationships with exposure metric day–evening–night level (DENL) and their confidence intervals. The Journal of the Acoustical Society of America 116 (2004) 334–343.
42. G.Q. Di, X.X. Zhou, X.W. Chen: Annoyance response to low frequency noise with tonal components: a case study on transformer noise. Applied Acoustics 91 (2015) 40–46.
43. J. Kaku, T. Kato, S. Kuwano, S. Namba: Predicting overall reaction to multiple noise sources. The Journal of the Acoustical Society of America 105 (1999) 1005.
44. J. Morel, C. Marquis-Favre, S. Viollon, M. Alayrac: Proposal for a simple model predicting the total annoyance due to industrial noises with low-frequency content mixed with industrial noises with a 100 Hz main component, in: International Congress on Noise Control Engineering, 2010.
45. T. Ronnebaum, B. Schulte-Fortkamp, R. Weber: Synergetic effects of noise from different sources: a literature study, in: Proceedings of Inter Noise, Liverpool, England, 1996, pp. 2241–2246.
46. S. Venturini, M. Plssem Mehmetoglu: A stata package for structural equation modeling with partial least squares. Journal of Statistical Software 88 (2019) 1–35.
47. S. Youssoufi, H. Houot, G. Vuidel, S. Pujol, F. Mauny, J.C. Foltête: Combining visual and noise characteristics of a neighborhood environment to model residential satisfaction: an application using GIS-based metrics. Landscape and Urban Planning 204 (2020) 103932.
48. C. Prasad Das, S. Goswami, B. Kumar Swain, M. Das: Association between traffic noise-induced psychophysiological, and socio-demographic factors of motorcycle riders. Applied Acoustics 196 (2022) 108898.
49. F. Liu, A. Chang-Richards, K.I.K. Wang, K.N. Dirks: Effects of indoor environment factors on productivity of university workplaces: a structural equation model. Building and Environment 233 (2023) 10098.
50. H.C. Indrani, S.N.N. Ekasiwi, D. Arifianto: Indoor soundscape model: assessing contextual factors in open-plan offices on university campuses in Surabaya, Indonesia. Building and Environment 237 (2023) 110267.
51. M.H. Beheshti, E. Taban, S.E. Samaei, M. Faridan, F. Khajehnasiri, L.T. Khaveh, M.B. Jebeli, A. Mehri, A. Tajpoor: The influence of personality traits and gender on noise annoyance in laboratory studies. Personality and Individual Differences 148 (2019) 95–100.

52. G. Di, Y. Yao, C. Chen, Q. Lin, Z. Li: An experiment study on the identification of noise sensitive individuals and the influence of noise sensitivity on perceived annoyance. Applied Acoustics 185 (2022) 108394.
53. H. Fastl, S. Kuwano, S. Namba: Accessing the railway bonus in laboratory studies. The Journal of the Acoustical Society of America 17 (1996) 139–147.
54. Q. Wang, W. Hongwei, C. Yang, G. Zhang: Developing multivariate models for predicting the levels of multidimensional critical reactions due to metro noise inside buildings. Applied Acoustics 200 (2022) 109083.
55. J. You, P.J. Lee, J.Y. Jeon: Evaluating water sounds to improve the soundscape of urban areas affected by traffic noise. Noise Control Engineering Journal 58 (2010) 477–483.
56. S. Dewar: Water features in public places-human responses. Grad. Dip. Landscape and Architecture thesis, Queensland University of Technology, Queensland, Australia, Vol. 5, 1990, pp. 104–143.
57. L.A. Gille, C. Marquis-Favre, R. Weber: Aircraft noise annoyance modeling: consideration of noise sensitivity and of different annoying acoustical characteristics. Applied Acoustics 115 (2017) 139–149.
58. M. Wen, H. Ma, C. Wang: Effect of spectral parameters on the elderly's urgency perception of auditory warning signals. Applied Acoustics 195 (2022) 108850.
59. J. Morel, C. Marquis-Favre, L.A. Gille: Noise annoyance assessment of various urban road vehicle pass-by noises in isolation and combined with industrial noise: a laboratory study. Applied Acoustics 101 (2016) 47–57.
60. M. Caniato, F. Bettarello, C. Schmid, P. Fausti: Assessment criterion for indoor noise disturbance in the presence of low frequency sources. Applied Acoustics 113 (2016) 22–33.
61. T. Cheung Chan, K. Che Lam: The effects of information bias and riding frequency on noise annoyance to a new railway extension in Hong Kong. Transportation Research Part D: Transport and Environment 13 (2008) 334–339.

Cite this article as: Wang Q. Hongwei W. Cai Y. Zhang Y. & Yang C. 2025. Influence and prediction mechanisms for discomfort and memory disturbance due to structure borne sound from a metro masked with fountain sound. Acta Acustica, **9**, 7. https://doi.org/10.1051/aacus/2024087.