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Subjective perception analysis of active noise control algorithms in an encapsulated structure: An experimental study

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ABSTRACT

This study investigates the subjective perception of active noise control (ANC) performance, focusing on how individuals evaluate the noise reduction provided by different ANC algorithms. While the performance of the ANC algorithms has already been evaluated using objective metrics, this study aims to assess their effectiveness from a subjective perspective. In a simulated vehicle interior created using a noise box, two ANC algorithms were tested: the normalized least-mean-square (NLMS) algorithm and the hybrid selective fixed-filter active noise control normalized least-mean-square (SFANC-NLMS) algorithm. Participants were exposed to 27 stimuli, which combined three types of noise (motorcycle, street, and train), three sound pressure levels (55, 65, and 72 dB(A)), and three ANC conditions (no control, NLMS, and SFANC-NLMS). Subjective evaluations were collected using three indicators: perceived annoyance (PAY), perceived affective quality (PAQ), and perceived loudness (PLN). These metrics captured participants' impressions of the noise environment and the impact of noise control. The study is structured around three research questions (RQ1, RQ2, and RQ3), each addressing different aspects of ANC performance evaluation. In response to RQ1, the results demonstrated that the SFANC-NLMS algorithm outperformed NLMS in reducing perceived annoyance and loudness. Regarding RQ2, higher sound levels (72 dB) led to greater perceived annoyance, but sound level did not significantly alter the relationship between ANC algorithm type and perceived annoyance. Finally, in addressing RQ3, noise type influenced ANC effectiveness, with SFANC-NLMS showing more significant reductions in perceived annoyance compared to NLMS. Overall, the findings confirm that the SFANC-NLMS algorithm provides better noise reduction in encapsulated structures.

1. Introduction

Active noise control (ANC) is an effective technique for reducing unwanted sound or vibrations by applying the principle of sound wave superposition. The idea concept is generating a secondary signal, known as "anti-noise," which has the same amplitude as the unwanted noise but is phase-inverted, resulting in significant noise cancellation [1,2]. For this cancellation to occur, ANC systems must accurately predict the noise signal's amplitude and phase at a specific spatial point. While the amplitude may remain steady, the phase changes dynamically over time due to the physical behavior of sound waves in space [3,4]. ANC has found applications in numerous fields, such as personal audio devices, vehicles, aircraft, building acoustics, home appliances, industrial equipment, medical devices, and maritime environments. These technologies are particularly valuable in enclosed spaces like car interiors, airplane cabins, and train compartments [5,6], where passive noise reduction methods such as sound-absorbing materials—are traditionally employed [7]. However, at low frequencies, passive approaches require substantial material mass and volume to achieve significant noise reduction, which can be impractical [8,9]. In contrast, ANC systems are well-suited to addressing low-frequency noise challenges in such settings. Low-frequency noise in vehicles primarily originates from structural vibrations caused by the engine and tires [10,11]. Engine noise is typically concentrated below 500 Hz, while vibrations from tires often result in structure-borne noise below 1 kHz. Additionally, cabin resonances tend to amplify these low-frequency sounds, further contributing to the noise level. Road noise, generated by the interaction between vehicle tires and the road surface, represents another major source of noise in automo-

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biles [12]. By addressing these challenges, ANC systems play a critical role in improving acoustic comfort and reducing noise pollution.

Traditional ANC systems typically rely on adaptive algorithms, such as the Filtered-X least-mean-square (FxLMS), to reduce noise due to their simplicity and robustness under standard conditions. However, these LMS-based algorithms exhibit slow convergence and limited tracking capability, making them less effective in handling dynamic or non-stationary noises commonly encountered in encapsulated structure where noise variability is high and user perception of noise reduction quality is critical [13,14]. Although other adaptive algorithms such as the Filtered-X Affine Projection (FxAP) and the Filtered-X Recursive Least Squares (FxRLS) offer improved convergence rates [15,16], their computational cost and sensitivity to modeling errors limit their applicability in real-time systems. Deep learning brings significant advancements to ANC by enabling models to adapt dynamically to complex, non-stationary noise patterns. Convolutional neural networks (CNNs) are effective in extracting robust features, eliminating the need for manually defined features that traditional algorithms rely on [17,18]. This automated feature extraction allows deep learning-based ANC systems to identify nuanced noise characteristics, offering better generalization across varying environments and noise types [19,20]. Building on these strengths, hybrid approaches like the selective fixed-filter active noise control (SFANC) combined with FxNLMS algorithm effectively combine deep learning with traditional adaptive control methods to overcome the limitations of each. In this setup, the CNN component dynamically selects the optimal pre-trained filter based on the noise type, while the FxNLMS algorithm adaptively fine-tunes the filter coefficients for real-time noise reduction. This synergy of SFANC-FxNLMS combines flexible filter selection with stable adaptive control, achieving faster response, enhanced noise reduction, and robustness in non-stationary environments such as vehicles and industrial settings [21].

Sound quality assessment has become a very active area of research, focusing on the subjective response that sounds (especially noise) evoke in humans, with the aim of achieving better sound design and noise enhancement techniques [22,23]. In particular, many studies have focused on the evaluation of sound quality in car interiors, examining different sound sources such as road noise, wind noise, and engine noise [24,25]. These studies highlight the complexity of the evaluation process, as each noise type has distinct characteristics, making it challenging to address all features simultaneously. Consequently, sound quality studies often focus on specific features, such as residual engine noise, which has been studied with active control. Results indicate that ANC is an effective tool for reducing low-frequency noise levels and improving acoustic comfort [26,27]. Studies have explored the perception of roughness in car engine noises using complex cepstrum analysis, underlining the importance of psychoacoustic parameters in designing sound profiles that align with user expectations [28]. While some experiments have been conducted in laboratory settings, further investigation is needed to fully understand ANC's impact on acoustic comfort inside vehicles. For instance, [29] designed an active tuning system to meet different engine sound quality requirements, and other methods have been explored for sound quality improvements with effectiveness demonstrated near virtual microphones [30,31] or error microphones [32,33]. Applied psychoacoustics is typically the foundation of sound quality evaluation [34,24], including in the automotive industry [35,36]. Psychoacoustic studies are often complemented by jury tests and mathematical models to estimate sound quality. Examples of sound quality studies on engine noise inside vehicles can be found in [37,38].

To address the research gap regarding the perception of active noise cancellation algorithms and their effects on noise perception in encapsulated structures, this study investigates the perceptual effects of active noise cancellation applied in a noise box simulating a vehicle interior. Specifically, this study compares a conventional NLMS algorithm with a modified version of SFANC-FxNLMS, called SFANC-NLMS, to investigate their influence on noise perception. The following research questions (RQ) are addressed:

- **RQ1.** To what extent do different ANC algorithms (NLMS and SFANC-NLMS) influence perceived annoyance across various noise types in a simulated vehicle environment?
- **RQ2.** Does sound level (55, 65, and 72 dB(A)) moderate the relationship between ANC algorithm type and perceived annoyance, altering the strength or direction of this association?
- **RQ3.** How do different noise sources (e.g., motorcycle, street, and train noises) interact with ANC algorithms and sound levels to shape perceived annoyance and overall acoustic comfort?

The paper is organized into five sections. Section 2 presents the context of this study by describing the environment of the control system and the algorithm used. Section 3 outlines the methodology employed to set up the experiment. Section 4 presents the results of the experiment. Section 5 provides a discussion of these results and answers the research questions. Finally, Section 6 concludes the paper.

2. Context of the study

2.1. Environment of control: noise box

The encapsulated structure, known as a noise box, is designed as a test platform for benchmarking vehicle interior noise. It is going to be a simplified interior noise investigation system coupled by a plate and a cavity. For example, this setup allows for the evaluation of materials, structures, and control strategies aimed at reducing noise inside a vehicle. The system must fulfill the following requirements:

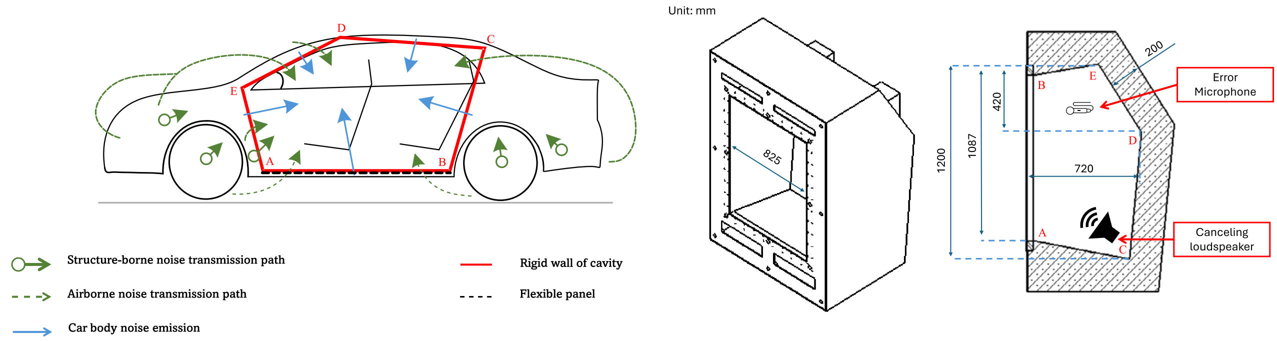
- The system must be representative, providing access to panel, cavity, structure-borne noise, airborne noise, and noise control measures.
- The system should be straightforward to model and analyze, with a simple geometry and clearly defined boundary conditions.
- All geometric, material, and physical parameters must be specified.

A simplified plate-cavity system, modeled as a rigid box with one flexible panel, is selected to design a Noise-Box for testing vehicle interior noise control, based on key criteria for representativeness, ease of modeling, and defined parameters. Using a passenger car as a reference, the Noise-Box geometry reflects the relationship between the plate-cavity system and a vehicle cabin. Interior noise, which includes sounds from the engine, tires, intake, exhaust, wind, and other sources, enters through either structure-borne or airborne paths, as shown in Fig. 1. In this model, the cavity simulates the cabin, and the panel represents the vibrating car body: structure-borne noise arises when the panel is mechanically excited, and airborne noise occurs when external sounds pass through the panel, illustrating the coupled dynamics of the structure and enclosed acoustic field.

All control paths are calculated in this environment. The primary path refers to the path of the unwanted noise from the source to the error microphone. The secondary path is the path between the actuator, in this case, a loudspeaker, and the error microphone where the control signal is sent to cancel the primary noise. The reference path is the path from the noise source to the reference sensor, in this case, an accelerometer, which detects the primary noise characteristics and provides input to the control system for noise cancellation. The reference accelerometer is positioned at the top-left corner of the aluminum panel to avoid nodal points. The loudspeaker used as the actuator is fixed inside the cavity, facing the plate. The error microphone is located at the inside of the cavity. All of these control paths are computed through an experiment outlined in Section 3.2.1.

2.2. Traditional algorithm: NLMS algorithm

The NLMS algorithm is an adaptive active noise control (ANC) algorithm. Due to the non-minimum phase nature of our experimental environment, the FxNLMS algorithm, which typically relies on secondary



(a) (b)

Fig. 1. The principle of noise in vehicle interiors and the panel-cavity system (a) and schematic diagram of the Noise Box for noise mitigation measures (b) [39].

path estimation, was found to be unsuitable for this study. A system is said to be non-minimum phase when it presents unstable zeros, i.e., zeros located outside the unit circle in the z-domain. These zeros result in an initial system response that moves in the opposite direction of the steady-state behavior, making control more challenging and often introducing phase-related delays. Non-minimum phase systems often lead to instability or reduced performance in ANC applications [40,41]. In practice, secondary path estimation is subject to modeling errors, which degrade control performance, particularly in experimental environments. Based on these considerations and the results from the NLMS algorithm, the FxNLMS algorithm was forgone in favor of the simpler NLMS algorithm, avoiding the complexities of secondary path estimation.

The control system is based on a feedforward architecture, with the input signal vector $x(n) = [x(n), x(n-1), \dots, x(n-N+1)]$ and the signal after the reference path $r(n)$ drive the NLMS control output $y(n)$:

$$y(n) = w^T(n)r(n) \tag{1}$$

where $w(n)$ represents the adaptive filter coefficient vector. The residual error signal, $e(n)$, defined as:

$$e(n) = d(n) - s(n) * (w^T(n)r(n)) \tag{2}$$

This error is minimized using the gradient descent method with step size μ. The NLMS update rule is:

$$w(n+1) = w(n) + \mu e(n)\frac{r(n)}{r^T(n)r(n) + \epsilon} \tag{3}$$

where T denotes the transpose operation, and ϵ is a small constant (set to 2.2204×10^{-16}) to avoid numerical instability during weight updates [42].

2.3. Novative algorithm: SFANC-NLMS algorithm

The hybrid SFANC-NLMS algorithm combines adaptive filtering with a dynamic filter selection mechanism that adjusts the control filter based on the type of noise. The algorithm operates with a set of pre-trained control filters, each optimized for different noise profiles. A 1D convolutional neural network (CNN) processes the incoming noise and selects the most appropriate control filter by outputting the index of the filter best suited to the current noise conditions. Once the optimal filter is chosen, the NLMS algorithm continuously updates its coefficients to minimize the error signal further. This adaptive adjustment occurs at the sampling rate, allowing the control filter to be fine-tuned in real time. By integrating the filter selection capabilities of the CNN with the adaptability of the NLMS algorithm, the system efficiently adapts to varying noise conditions. This approach is presented in more detail in [43].

The simulation parameters are as follows: The ANC system operates in a single-channel configuration with a sampling rate of 16 kHz, and the control filter length is set to 4096 taps. The system utilizes state-space coefficients for the reference, primary, and secondary paths. Seven pre-trained control filters were used, corresponding to seven different white noise signals with the following frequency ranges: 20–2000 Hz, 20–1000 Hz, 1000–2000 Hz, 20–500 Hz, 500–1000 Hz, 1000–1500 Hz, and 1500–2000 Hz. The NLMS algorithm was employed to derive the optimal control filters for these noises, with a stepsize of 0.0001.

3. Methodology

3.1. Study site, participants and administration

The experiment was conducted in a study room at Central House, chosen for its quiet environment, where participants used paper and pencil to complete the tasks as presented in Fig. 2. Formal ethical approval was approved by BSEER Local Research Ethics Committee at University College London prior to participant recruitment and the commencement of the experiment. Each participant was informed about the study context through a Participant Information Sheet before taking part, and consent was obtained via a form at the beginning of the experiment.

A total of 35 participants, including 16 men and 19 women, aged 23 to 62 (mean age around 31), were recruited. Two participants were deemed unreliable due to a Spearman coefficient of 0.8 and a p-value over 20%.

3.2. Stimuli

3.2.1. Experimental setup for stimuli design in the noise box

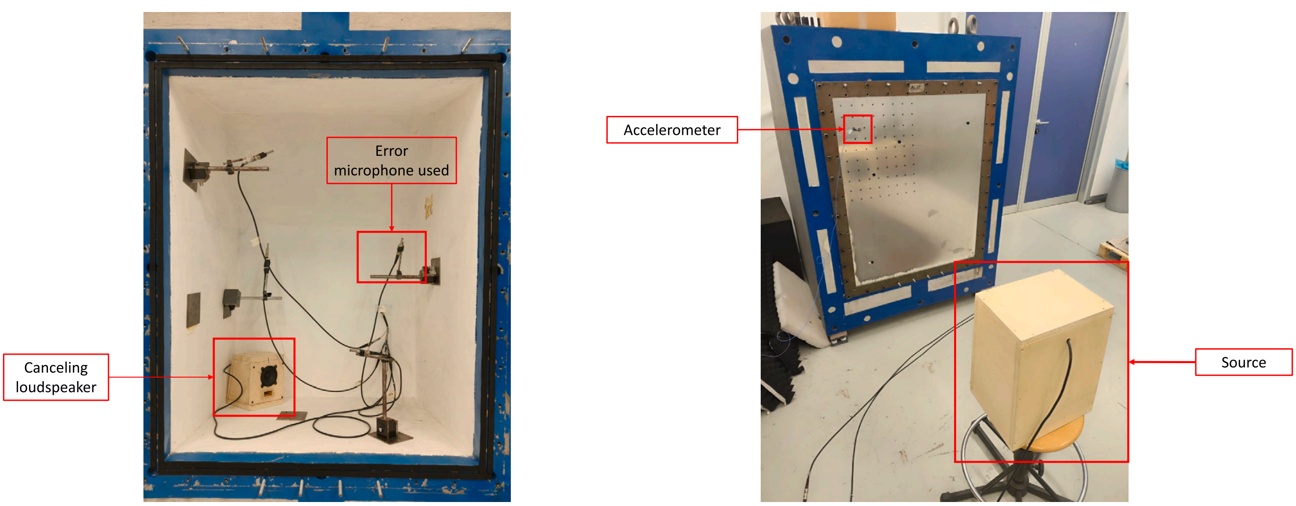
The stimuli design for the jury test relies on the experimental setup of the noise box, as introduced in Section 2.1. This setup includes a sealed cavity, where the opening is closed with an aluminum plate to isolate and focus acoustic interactions. The noise box is equipped with components to extract the frequency response functions (FRFs) of the reference, primary, and secondary paths, to characterize the acoustic behavior of the system. Fig. 3 illustrates this configuration, showcasing the internal and external arrangement.

Two speakers are utilized in this setup. An external speaker simulates disturbances outside the cavity, while an internal speaker generates the "anti-noise" signal, it is called a canceling loudspeaker. Both speakers are driven by random noise signals generated by a computer and transmitted through the data acquisition system. Inside the cavity, four microphones are placed to capture acoustic responses, though only one microphone is employed for this single-channel control algorithm experiment. An accelerometer, positioned at the top left corner of the panel to avoid nodal points, acts as the reference sensor by capturing noise vibrations before they enter the cavity.

The measurement equipment includes a PCB 130E20 microphone with a sensitivity of 37.37 mV/Pa, calibrated using a Bruel & Kjaer 4231

(a) (b)

Fig. 2. Illustration of Participant Participation. (a) shows how the participant filled out the questionnaire, and (b) depicts the room where the experiment took place.



(a) (b)

Fig. 3. Images of the experimental set-up from inside (a) and outside (b).

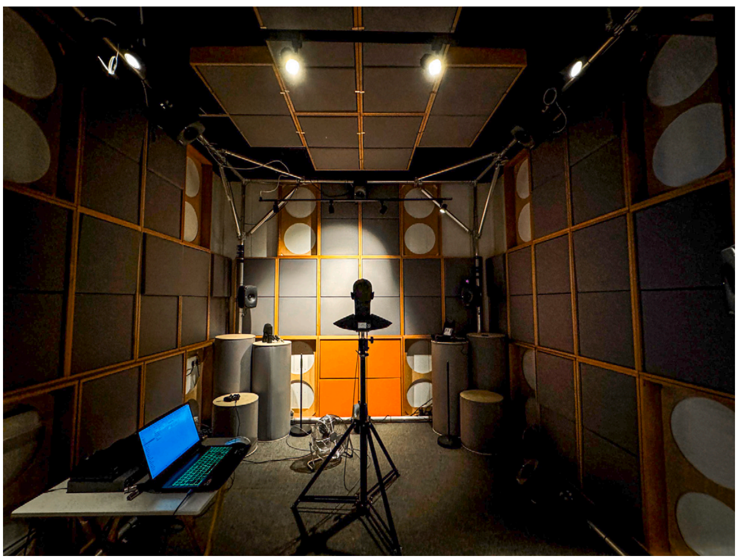
calibrator providing a reference frequency of 1 kHz and a sound pressure level of 94 dB. An accelerometer, the PCB 333B30 model with a sensitivity of 99.6 mV/g (10.16 mV/m/s^2), is connected to a PCB Piezotronics model 483C series signal conditioner, interfacing with a National Instruments NI cDAQ-9178 data acquisition system. These devices ensure accurate measurements of both acoustic and vibratory signals.

The FRFs were derived in two phases. First, the external speaker was activated to measure the reference path, with the input being the voltage signal to the speaker and the output being the accelerometer signal (m/s^2), resulting in an FRF magnitude in m $\cdot$ V/s^2. Next, the internal speaker was used to compute both the primary and secondary path FRFs. The primary path was calculated using the external speaker's input voltage and the cavity microphone signal as output (Pa/V), while the secondary path was derived similarly but with the internal speaker as the input source. All FRFs were computed over a frequency range of 100 Hz to 2000 Hz, with a sampling rate of 16,000 Hz. Additionally, the acoustic characteristics of the laboratory, influenced by surrounding materials, shaped the behavior of the sound field. These factors were accounted for when analyzing the experimental data.

To replicate real-world scenarios, three types of noise, motorbike, train, and street sounds, were selected from a publicly available dataset [44]. These noises were filtered through the state-space model derived from the FRFs of the noise box, ensuring realistic acoustic behavior. The FRFs also enabled the derivation of the state-space coefficients needed to model the acoustic dynamics of the noise box, a critical step for implementing active noise control. In the experimental design, three ANC conditions (off, NLMS, and SFANC-NLMS) were tested with the three noise types at three sound pressure levels (55 dB(A), 65 dB(A), and 72 dB(A)), resulting in $3 \times 3 \times 3 = 27$ stimulus combinations. Additionally, a train noise condition at 65 dB(A) was included as a control to as-

Table 1
Mean and standard deviation of the measured LAeq levels for each noise type and control condition. The first line is the level on the left side of the HATS and the second one is the right sides.

Noise Type	Control: OFF			Control: NLMS			Control: SFANC-NLMS		
	72 dB(A)	65 dB(A)	55 dB(A)	72 dB(A)	65 dB(A)	55 dB(A)	72 dB(A)	65 dB(A)	55 dB(A)
Train	73.4 ± 0.3	67.1 ± 0.5	56.4 ± 0.6	73.0 ± 0.3	67.3 ± 0.4	56.2 ± 0.1	68.3 ± 0.4	63.1 ± 0.3	50.2 ± 0.2
	73.0 ± 0.3	67.0 ± 0.4	55.4 ± 0.6	73.4 ± 0.6	67.9 ± 0.6	56.4 ± 0.1	69.2 ± 0.5	63.1 ± 0.4	50.0 ± 0.2
Moto	70.3 ± 0.3	66.3 ± 0.2	56.4 ± 0.3	69.3 ± 0.1	63.9 ± 0.1	54.8 ± 0.3	62.8 ± 0.3	58.1 ± 0.3	48.8 ± 0.4
	70.2 ± 0.2	66.3 ± 0.3	56.5 ± 0.3	68.9 ± 0.3	63.4 ± 0.3	54.7 ± 0.3	62.7 ± 0.3	58.5 ± 0.4	48.5 ± 0.3
Street	72.0 ± 0.7	64.3 ± 0.4	57.3 ± 0.4	72.2 ± 0.3	64.1 ± 0.4	56.9 ± 0.3	67.3 ± 0.4	61.8 ± 0.3	54.6 ± 0.3
	71.4 ± 0.6	64.3 ± 0.3	57.5 ± 0.4	72.1 ± 0.3	64.2 ± 0.3	57.4 ± 0.3	67.4 ± 0.4	61.8 ± 0.4	54.6 ± 0.3


(a)

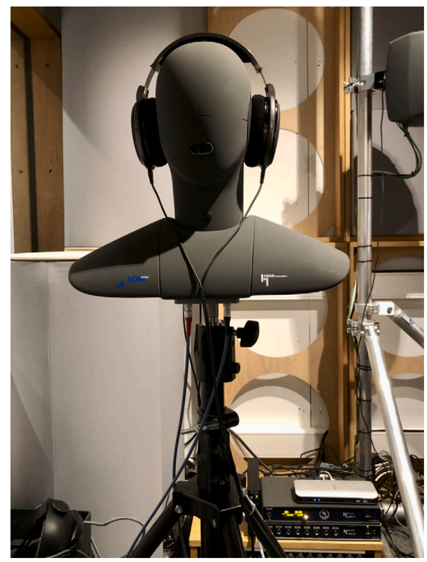

(b)

Fig. 4. Interior view of the Audio Lab with the HATS setup (a), and the HATS setup during the calibration (b).

sess test–retest reliability, bringing the total to 28 unique stimuli for the study.

3.2.2. Calibration

The calibration was conducted in an Audio Lab, using a Head and Torso Simulator (HATS) HEAD acoustics HMS II.3 LN HEC with Sennheiser HD 650 headphones. Before calibrating the stimuli, the HATS was initially calibrated with a Larson Davis CAL250 sound level calibrator, emitting a 251.2 Hz tone at 114 dB. Each stimulus, played through a computer, was calibrated individually. Volume settings were adjusted to achieve the desired noise levels of 55 dB(A), 65 dB(A), and 72 dB(A). These levels were calibrated without the application of active noise control. For stimuli with control applied, the volume parameters were adjusted according to the corresponding noise level. ArtemiS SUITE 12 software was used for the calibration, along with the labO2-V1 playback equalizer and the HDA IV headphone amplifier. To account for variability in noise levels due to headphone positioning, each stimulus was calibrated three times with the headphones repositioned on the HATS between each measurement to capture uncertainty. The results of the measured noise levels after calibration are shown in Table 1, and photographs of the experiment setup are provided in Fig. 4.

3.3. Experiment design

The participants were first required to provide basic information: gender and age, along with a pre-test assessment of (1) individual noise sensitivity (INS) via the Weinstein Sensitivity to Sound Scale, 5-item version (WSSN-5) [45]; (2) a baseline noise annoyance (BNA) based on ISO/TS 15666 [46] using the version of the questionnaire presented in [47]; and (3) the Perceived Stress Scale (PSS-4) [48]. The pre-test questionnaires were selected to assess potential confounding factors such as stress and mood on soundscape perception [49,50]. The pre-test assessment questionnaire is presented in Table A.1 in Appendix A.

After completing the basic data and pre-test assessment, a brief training session was conducted to familiarize participants with the stimuli and questionnaire. During training, the participants were first exposed to the loudest stimulus, followed by the quietest stimulus, and then a training noise (a train noise at 65 dB(A)). After hearing the training noise, participants were required to answer questions. Stimuli were played through a sound sequence design using the software FL Studio.

For test–retest reliability, an unfiltered 65 dB(A) train noise was used as the first and last stimulus for each participant, without replicating the noise box behavior. The other 27 stimulus combinations were presented in random order to all participants. Participants were allowed to listen to each stimulus as much as they wanted, with an experimenter available to replay stimuli if needed. All stimuli presented to the participants were recorded and played back.

Each stimulus was evaluated based on (1) perceived annoyance (PAY), (2) perceived affective quality (PAQ), and (3) perceived loudness (PLN). In contrast to the pre-test assessment of annoyance in the absence of acoustic stimuli, the assessment of PAY referred specifically to the noise in the presented stimulus. The question asked: *Thinking about the noise you just heard, how much does the noise bother, disturb, or annoy you?* Responses were divided into 5 items, ranging from “Not at all” to “Extremely” [46].

The PAQ (Perceived Affective Quality) attributes proposed in ISO/TS 12913-2 were adopted to structure the evaluation of affective responses to the indoor soundscape as modified by the stimuli. The PAQ consists of 8 attributes (i.e., eventful, vibrant, pleasant, calm, uneventful, monotonous, annoying, chaotic), forming an octant circumplex model (International Organization for Standardization, 2019 [51]). Participants were asked to visually position a mark on a 2D map representing these attributes. The question asked: *Thinking about the sound you just heard, where would you place the surrounding sound environment on this scale?* This method allows participants to express their affective response to the sound environment, accounting for both its emotional tone and complexity.

To assess loudness (PLN), a relative magnitude estimation method was adopted. Participants were instructed to estimate the loudness of the stimulus under test (SUT). A numerical score was assigned to each stimulus based on its perceived loudness. The question asked: *How loud would you say the sound environment is?* The scale ranged from 0 to 100, allowing for a nuanced assessment of loudness perceived by the participant [52]. The noise evaluation questionnaire is presented in Table A.2 in Appendix A.

3.4. Data analysis

The data were processed to obtain the mean scores and standard deviations for each indicator: INS, PSS-4, and BNA. For the INS and PSS-4 indicators, each participant's score was calculated by summing the scores for all responses given to the questions and dividing this sum by the total number of questions in the respective questionnaire. Specifically, the INS questionnaire consists of 5 questions, and the PSS-4 questionnaire consists of 4 questions. The global mean score for each indicator was then calculated by averaging the individual participant scores. Standard deviations were computed to assess the variability of participants' scores around the mean.

For the BNA indicator, the data were organized by noise type (e.g., traffic, airplane, train, etc.). Each participant's score for each noise type was calculated in the same manner, by summing the responses to the relevant questions and dividing by the number of questions for that noise type. The mean and standard deviation were then calculated for each noise type based on the participants' scores. These means and standard deviations provide an overview of participants' perceptions regarding different noise types and indicators.

A three-way repeated measures ANOVA (3WR-ANOVA), followed by a post-hoc Tukey HSD test, was conducted to evaluate perceived annoyance (PAY), with the numerical scale of annoyance as the dependent variable and three independent variables (i.e., noise type, noise levels, and ANC condition). Prior to conducting the analysis, we verified that the assumptions of normality, homogeneity of variances, and sphericity were met. The normality of residuals was assessed using the Shapiro-Wilk test [53], homogeneity of variances was tested with Levene's test [54], and sphericity was tested using Mauchly's test [55]. All assumptions were satisfied, allowing us to proceed with the 3WR-ANOVA. The circumplexity of the PAQ attributes was examined to assess the generalizability of the PAQ model. Furthermore, a three-way repeated measures permutational multivariate analysis of variance (3WR-PERMANOVA) was conducted using a distance matrix as input. This method was chosen because the PAQ data did not follow a normal distribution, as indicated by Mardia's multivariate normality tests [56]. The analysis considered ISOPL, the x-coordinate of the participant's mark on the 2D PAQ map, and ISOEV, the y-coordinate, as the dependent variables. The independent variables included noise levels, control conditions, and noise types. Post-hoc pairwise comparisons were performed using the pairwise.adonis() function, based on the ADONIS (permutational multivariate analysis of variance) method, to examine the differences between factor levels across all combinations of noise types, control conditions, and noise levels. This procedure was employed to identify significant pairwise differences between the groups following the main analysis.

For perceived loudness (PLN), a three-way repeated measures ANOVA (3WR-ANOVA), followed by a post-hoc Tukey HSD test, was conducted to evaluate perceived loudness, with the numerical scale of loudness as the dependent variable and three independent variables (i.e., noise type, noise levels, and ANC condition). Similar to the PAY analysis, various tests were performed on the data to check if all assumptions were satisfied in order to use the 3WR-ANOVA.

4. Results

4.1. Pre-test assessment

The mean value for the INS indicator is 6.49 with a standard deviation of 2.20, which indicates that the participants on average experience a medium to high level of noise pollution in their environment. As the INS scale ranges from 1 to 10, this value is in the upper mid-range of the scale and indicates a medium to high sensitivity to noise among the participants. In contrast, the mean value for PSS-4, which measures perceived stress, is 3.12 with a standard deviation of 0.75. As the scale for this indicator ranges from 0 to 4, this value indicates that the participants experience a medium level of stress on average, with some variability in the responses, but without reaching an extreme level of stress.

The mean scores for each type of noise, as measured by the BNA, vary slightly. The highest mean score was recorded for road traffic noise with a value of 2.37, suggesting that, on average, this noise type is perceived as somewhat disturbing. The lowest mean score was recorded for animals noise with a value of 1.51, indicating that participants generally find animal-related noises less disturbing. The other noise types, including airplane, train, children, and other people have mean scores ranging from 1.86 to 2.09, reflecting a moderate level of disturbance for these sounds. In terms of standard deviations, road traffic and airplane have the highest variability, with standard deviations of 1.14 and 1.19, respectively, indicating that responses to these noises are more diverse. The animals and other people categories show the lowest variability, with standard deviations of 0.95, suggesting more consistent perceptions of these noise types across participants. Overall, these results show moderate variability in how different noise types are perceived by participants.

4.2. Perceived annoyance

The results of the three-way repeated ANOVA (3WR-ANOVA) indicate that the control condition, noise type, and noise level all have significant effects on the perceived annoyance of participants, with some interactions between these factors revealing more complex relationships. In this analysis, the F-value reflects the ratio of variance explained by each factor to the unexplained variance (residual error). A higher F-value indicates a greater influence of the corresponding factor on perceived annoyance. The p-value represents the probability that the observed effect occurred by chance, with values below the significance threshold (typically 0.05) indicating a statistically significant effect. In this study, all p-values have been adjusted using the False Discovery Rate (FDR) correction to account for multiple comparisons. The control condition shows a particularly strong effect ($F = 44.48, p < .0001$), suggesting that different noise control strategies significantly influence how participants perceive noise. Similarly, noise level has a major impact ($F = 161.4, p < .0001$), with higher levels of noise leading to greater perceived annoyance. Noise type also contributes significantly ($F = 5.336, p = .007$), indicating that different types of sounds (e.g., street, train, or motorbike noise) have varying impacts on participants' experiences. When examining interactions, the combination of control condition and noise type is significant ($F = 4.859, p = .0015$), suggesting that the effectiveness of noise control methods differs depending on

Table 2
Results of the three-way repeated measures ANOVA (3WR-ANOVA) for PAY.

Comparison	F	p-value (FDR)
Noise Types	5.33	0.007 *
ANC	44.48	< 0.0001 ****
Noise Levels	161.4	< 0.0001 ****
Noise Types × Control Conditions	4.86	0.0015 **
Noise Types × Noise Levels	7.93	< 0.00001 ****
Control Conditions × Noise Levels	1.83	0.126
Noise Types × Control Conditions × Noise Levels	3.47	0.0008 ***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$.

the type of noise present. This highlights that noise control strategies may need to be tailored to specific noise sources to achieve optimal results. Additionally, the interaction between noise type and noise level is significant ($F = 7.926, p < .0001$), implying that the combined characteristics of the noise (both type and intensity) play an important role in the perceived annoyance of the participant. However, the interaction between control condition and noise level ($F = 1.831, p = .126$) does not show significant effects, meaning that noise control effectiveness is relatively consistent across different noise levels. Finally, the three-way interaction between control condition, noise type, and noise level is significant ($F = 3.47, p = .0008$), indicating that these factors do not operate independently but interact in ways that can influence noise perception in more complex ways. These findings underscore the importance of considering multiple factors together when designing noise control strategies, as their combined effects can vary depending on the specific noise characteristics. Results of the 3WR-ANOVA are findable in Table 2.

Following results obtained with the post hoc Tukey HSD, significant differences in the perceived noise annoyance were observed across different noise types, control conditions, and sound levels. The effect size d complements the p-value by quantifying the magnitude of the difference between two conditions. This allows a better understanding of the practical significance of observed differences beyond mere statistical significance. Regarding noise types, the comparison between motorbike and street shows a highly significant difference with a moderate effect size noted d ($p = .005, d = -0.27$), indicating that motorbike noise is perceived differently from street noise. However, the comparisons between motorbike and train ($p = .370, d = -0.11$) and street and train ($p = .147, d = .15$) show no significant differences, suggesting relative similarity between these noise types in terms of perceived annoyance. For the control conditions, all comparisons are extremely significant ($p < .0001$ or $p < .001$), with effects ranging from moderate to strong. SFANC-NLMS provides a notable improvement compared to No Control ($d = -0.53$) and NLMS ($d = -0.31$), confirming the superior effectiveness of this new algorithm. The No Control condition differs significantly from NLMS ($d = 0.22$), although the effect size is smaller, highlighting some improvement with NLMS. The interactions between noise types and control conditions reveal marked differences. For instance motorbike with SFANC-NLMS significantly differs from street with No Control ($p < .0001, d = -0.98$), while moderate to strong effects are observed for other combinations. These results underscore the importance of interactions between noise type and algorithm effectiveness. Finally, the three-way interactions between noise levels, noise types, and control conditions reveal interesting patterns. For example, for motorbike noise at 55 dB, SFANC-NLMS is perceived as substantially more effective than No Control at 72 dB ($d = 2.20$), indicating that the improvement provided by the algorithm can offset a higher noise level. These interactions demonstrate that the perceived effectiveness of the algorithms varies depending on the specific combination of noise type, sound level, and control condition, highlighting the need to tailor noise reduction strategies to these factors. Results of the post hoc Tukey HSD are findable in Table 3.

Table 3
Post hoc Tukey HSD results for significant comparisons in the PAY study.

Comparison	p-value	Effect
Moto vs. Street	0.005	-0.27
Moto vs. Train	0.37	-0.1111
Street vs. Train	0.15	0.16
SFANC-NLMS vs. No Control	< 0.0001 ****	-0.53
SFANC-NLMS vs. NLMS	< 0.0001 ****	-0.31
No Control vs. NLMS	0.0006 ***	0.22
55 dB vs. 65 dB	< 0.0001 ****	-0.75
55 dB vs. 72 dB	< 0.0001 ****	-1.43
65 dB vs. 72 dB	< 0.0001 ****	-0.69
Moto (SFANC-NLMS) vs. Street (No Control)	< 0.0001 ****	-0.98
Street (No Control) vs. Train (SFANC-NLMS)	< 0.0001 ****	+0.77
Moto (SFANC-NLMS) vs. Moto (No Control)	< 0.0001 ****	-0.60
Moto (55 dB) vs. Moto (72 dB)	< 0.0001 ****	-1.54
Moto (55 dB) vs. Street (72 dB)	< 0.0001 ****	-1.75
Moto (55 dB) vs. Train (72 dB)	< 0.0001 ****	-1.71
Train (55 dB) vs. Street (72 dB)	< 0.0001 ****	-1.65
Train (55 dB) vs. Train (72 dB)	< 0.0001 ****	-1.61
SFANC-NLMS (55 dB) vs. SFANC-NLMS (72 dB)	< 0.0001 ****	-1.51
SFANC-NLMS (55 dB) vs. No Control (72 dB)	< 0.0001 ****	-1.88
SFANC-NLMS (55 dB) vs. NLMS (72 dB)	< 0.0001 ****	-1.79
NLMS (55 dB) vs. No Control (72 dB)	< 0.0001 ****	-1.62
NLMS (55 dB) vs. NLMS (72 dB)	< 0.0001 ****	-1.53
SFANC-NLMS (Moto, 55 dB) vs. No Control (Street, 72 dB)	< 0.0001 ****	2.20
SFANC-NLMS (Moto, 55 dB) vs. NLMS (Train, 72 dB)	< 0.0001 ****	2.03
NLMS (Moto, 55 dB) vs. No Control (Street, 72 dB)	< 0.0001 ****	2.11
SFANC-NLMS (Train, 55 dB) vs. No Control (Street, 72 dB)	< 0.0001 ****	2.23

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$.

4.3. Perceived affective quality

4.3.1. Circumplex circles

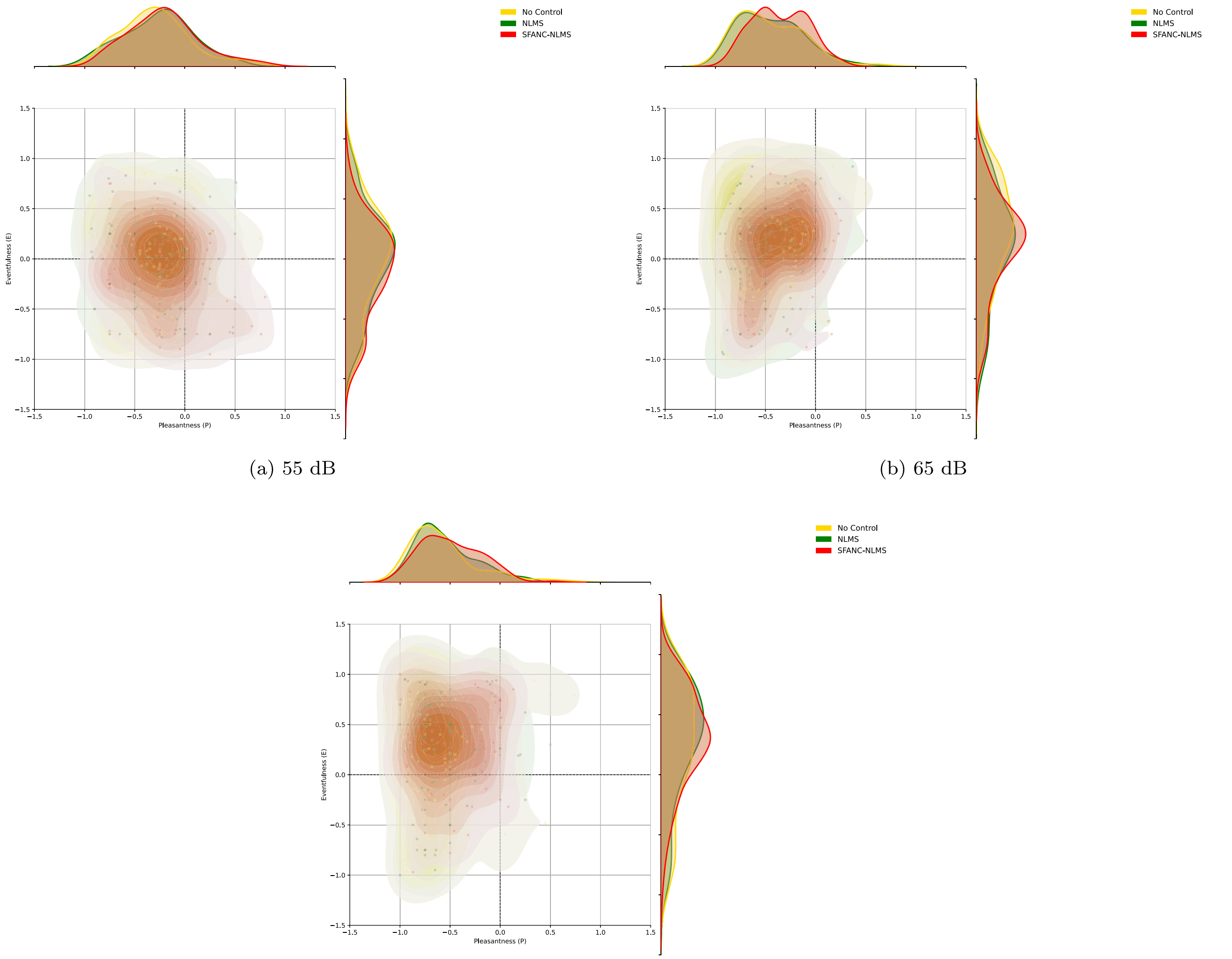
Regarding the distribution of points on the circumplex circles, we decided to merge results obtained with different types of noise to highlight the influence of the control condition. Fig. 5 displays plots of circumplex circles at various noise levels (55, 65, 72 dB(A)). Noises are generally perceived as chaotic, especially at higher sound levels. This perception can be attributed to two main factors. First, filtering each noise to replicate the behavior of the noise box amplifies the aluminum plate's acoustic response, adding a distinctive resonant character to the stimuli. Second, the original noises themselves are inherently eventful, characterized by dynamic and varied sound patterns. These two aspects contribute to an increased perception of eventfulness and a reduced sense of pleasantness, particularly at higher intensities.

As sound levels increase, the distribution of responses shifts toward the upper-left quadrant of the circumplex space—indicative of a more chaotic and unpleasant perceptual evaluation. Naturally, stimuli with lower sound levels are generally perceived as more pleasant, aligning with the typical relationship between sound intensity and subjective annoyance.

Regarding the control condition, the shape and position of the density clouds visible through the kernel density estimates on the x (pleasantness) and y (eventfulness) axes indicate that applying SFANC-NLMS makes the noise perceived as more pleasant and less eventful across all noise levels. This pattern suggests that the algorithm improves the affective quality of the soundscape, shifting it toward the bottom-right quadrant, which corresponds to calmer and more pleasant environments.

4.3.2. Three way repeated PERMANOVA

The results of the three-way repeated-measures PERMANOVA revealed several significant effects concerning the influence of the factors noise type, control condition, and noise level on the dependent variables ISOPL and ISOEV, as well as their interactions. The effect of noise type was highly significant ($F = 11.17, p = .001$), indicating that the



(a) 55 dB

(b) 65 dB

(c) 72 dB

Fig. 5. Density plots of eventfulness (ISOEV) as a function of pleasantness (ISOPL). Plots are shown separately for (a) 55 dB(A) (b) 65 dB(A) and (c) 72 dB(A).

type of noise strongly influences the dependent variables, independent of the other factors. This confirms that different noise types lead to distinct perceptual differences. Similarly, the effect of control condition was significant ($F = 9.35, p = .001$), suggesting that different control strategies influence participants' perceived affective quality. While this effect is notable, it is slightly lower than that of noise type. The noise level effect was also highly significant ($F = 13.50, p = .001$), demonstrating that increasing noise intensity (55, 65, 72 dB) significantly impacts participants' perception. This confirms that noise level is a key determinant of perceived affective quality. Unlike the initial analysis, the interactions between the factors also reached significance. The interaction between noise type and control condition ($F = 10.01, p = .001$) suggests that the effect of noise type varies depending on the applied control strategy. The interaction between noise type and noise level ($F = 14.00, p = .001$) reveals that the impact of noise type is modulated by its intensity. Additionally, the interaction between control condition and noise level ($F = 12.07, p = .001$) suggests that the effectiveness of control strategies depends on noise intensity. Finally, the three-way interaction between noise type, control condition, and noise level was also significant ($F = 10.43, p = .001$). This indicates that the combined effect of all three factors significantly influences participants' perception, meaning that noise type, control conditions, and noise level interact in a complex way to shape perceived affective quality. Results of the three-way repeated PERMANOVA are presented in Table 4.

Table 4
Results of the three-way repeated measures PERMANOVA (3WR-PERMANOVA) for PAQ.

Comparison	F	p-value
Noise Types	11.17	0.001 **
ANC	9.35	0.001 **
Noise Levels	13.50	0.001 **
Noise Types × Control Conditions	10.01	0.001 **
Noise Types × Noise Levels	14.00	0.001 **
Control Conditions × Noise Levels	12.07	0.001 **
Noise Types × Control Conditions × Noise Levels	10.43	0.001 **

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$.

The results of the post hoc pairwise revealed significant perceptual differences across several conditions. Specifically, the comparison between the motorbike and street noise types showed a substantial difference in affective quality ($p = .003, d = -0.120$), indicating that participants found the motorbike noise to be perceived as more unpleasant or intrusive compared to the street noise. Similarly, the comparison between street and train also revealed a significant difference ($p = .003, d = .090$), suggesting that the street noise was perceived more positively compared to the train noise, with an increased sense of unpleasantness for the train noise. In contrast, the comparison between motorbike and train noise types ($p = .021, d = -0.030$) did not reveal a

Table 5
Post-hoc pairwise comparisons results using the ADONIS method for significant comparisons in the PAQ study.

Comparison	p-value	Effect
Moto vs. Street	0.003 **	-0.12
Moto vs. Train	0.021 *	-0.03
Street vs. Train	0.003 **	0.09
NLMS vs. No Control	1.000	-0.03
NLMS vs. SFANC-NLMS	0.056	0.168
No Control vs. SFANC-NLMS	0.011 *	0.03
55 dB vs. 65 dB	0.003 **	-0.09
55 dB vs. 72 dB	0.003 **	-0.24
65 dB vs. 72 dB	0.003 **	-0.153
Moto (NLMS) vs. Street (No Control)	0.036 *	-0.2
Street (No Control) vs. Train (No Control)	0.036 *	0.19
Street (No Control) vs. Moto (SFANC-NLMS)	0.036 *	0.23
Street (No Control) vs. Train (SFANC-NLMS)	0.04 *	0.172
Moto (55 dB) vs. Street (72 dB)	0.036 *	-0.36
Street (72 dB) vs. Train (55 dB)	0.036 *	0.37
NLMS (55 dB) vs. No Control (72 dB)	0.036 *	-0.26
NLMS (55 dB) vs. NLMS (72 dB)	0.036 *	-0.25
No Control (72 dB) vs. SFANC-NLMS (55 dB)	0.036 *	0.26
SFANC-NLMS (55 dB) vs. NLMS (72 dB)	0.036 *	-0.26

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$.

significant perceptual difference after correction, suggesting that these two noise types were perceived similarly in terms of affective quality by the participants. Regarding control conditions, a significant difference was observed between the No Control and SFANC-NLMS conditions ($p = .011, d = .033$). This indicates that the SFANC-NLMS algorithm provided some improvement in the perceived affective quality of the noise environment, although the effect size was relatively small. In terms of noise levels, several significant differences were found. The comparison between 55 dB and 65 dB ($p = 0.003, d = -0.090$), 55 dB and 72 dB ($p = .003, d = -0.240$), and 65 dB and 72 dB ($p = .003, d = -0.153$) all revealed a significant impact on the perceived affective quality. The higher the noise level, the more negative the affective perception became, with 72 dB generally being perceived as the most unpleasant or disturbing, followed by 65 dB and 55 dB. Several other comparisons, such as those involving noise types (Moto vs. Street, Street vs. Train) and noise levels (55 dB vs. 72 dB, 65 dB vs. 72 dB), also showed statistically significant differences. These results indicate that participants were able to detect clear and meaningful differences in how different types of noise and noise levels affected their emotional response, providing valuable insights into the subjective affective perception of different acoustic environments. The detailed results of the post hoc comparisons are presented in Table 5.

4.4. Perceived loudness

The results of the three-way repeated measures ANOVA revealed that the control condition, noise type, and noise level all have significant effects on the perceived loudness of participants. A highly significant effect was found for noise types ($F = 9.739, p = .00019$), suggesting that the different categories of noise (e.g., motorcycle, street, train) have a substantial impact on the perceived loudness. This indicates that perceived loudness varies depending on the type of noise, with some types being perceived as more intense or disturbing than others. The main effect of noise control conditions was extremely significant ($F = 41.29, p < .0001$), highlighting the strong influence of noise control algorithms on the perceived loudness. The results indicate that these algorithms significantly reduce the perceived loudness of the noise, regardless of its type, showing their effectiveness in mitigating noise. Similarly, noise level has a major impact ($F = 63.1, p < .0001$), confirming that higher noise levels (55 dB, 65 dB, 75 dB, etc.) lead to stronger perceptions of loudness, with louder sounds being perceived as more disturbing. In terms of interactions, a significant interaction between noise types and control conditions was observed ($F = 5.171, p = .000658$), indicating that the effect of noise types on perceived loudness depends on the control algorithm used. A significant interaction between noise types and noise levels was also found ($F = 7.934, p < .0001$), showing that the effect of noise levels on perceived loudness differs according to the type of noise. On the other hand, the interaction between control conditions and noise levels was not significant ($F = 1.107, p = .356$), suggesting that noise levels did not significantly affect the effectiveness of the control algorithms in terms of perceived loudness. Lastly, a significant three-way interaction was found ($F = 2.649, p = .00821$), indicating that the combined effect of noise types, noise levels, and control conditions on perceived loudness is complex, with each factor influencing the others in a nonlinear way. Overall, the analysis revealed that all three factors—noise types, noise control conditions, and noise levels—have significant effects on perceived loudness, with complex interactions between them. The results emphasize the importance of considering these factors together when studying noise perception and developing noise control strategies. Results of the 3WR-ANOVA are findable in Table 6.

Table 6
Three-way repeated ANOVA results showing F-values, p-values, and significance levels for main effects and interactions for the PLN.

Comparison	F	p-value
Noise Types	9.74	< 0.001 ***
ANC	41.29	< 0.0001 ****
Noise Levels	63.1	< 0.0001 ****
Noise Types × Control Conditions	5.171	0.0007 ***
Noise Types × Noise Levels	7.93	< 0.0001 ****
Control Conditions × Noise Levels	1.11	0.36
Control Conditions × Noise Types × Noise Levels	2.65	0.008 **

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$.

The post hoc analysis using the Tukey HSD method reveals significant differences in the study of perceived loudness (PLN) between groups based on noise level, noise type, and control conditions. Regarding noise type comparisons, a significant difference was observed between motorbike and street ($p = .021, d = -2.917$), suggesting distinct PLN levels between these two types. A highly significant difference was also found between motorbike and train ($p = .00012, d = -4.6603$), indicating a pronounced distinction in perception. However, no significant difference was detected between street and train ($p = 0.24, d = -1.743$), reflecting a relative similarity in the perceived loudness. For noise control conditions, the SFANC-NLMS algorithm demonstrated a highly significant reduction in PLN compared to No Control ($p < 0.0001, d = -8.473$), showcasing its strong efficacy. Additionally, SFANC-NLMS outperformed NLMS with a significant improvement ($p = 2.37 \times 10^{-6}, d = -5.1047$). While NLMS also showed a significant reduction in PLN compared to No Control ($p = 0.00179, d = -3.3682$), it remains less effective than SFANC-NLMS. Significant differences were also observed across all pairwise comparisons of noise levels (55 dB, 65 dB, and 72 dB), with $p < 0.0001$. The effect sizes were -11.968 for 55 dB vs. 65 dB, -22.419 for 55 dB vs. 72 dB, and -10.451 for 65 dB vs. 72 dB. These findings confirm that PLN increases systematically with rising noise levels. When considering interactions between noise type, level, and control conditions, highly significant differences were observed ($p < 0.0001$) with effect sizes reaching up to -35.086. This demonstrates the cumulative influence of these factors on PLN. In extreme conditions, such as comparing SFANC-NLMS (Moto, 55 dB) to No Control (Train, 72 dB), the differences were strikingly significant ($p = 1.77 \cdot 10^{-11}, d = -35.086$), emphasizing the substantial impact of the SFANC-NLMS algorithm, particularly when noise type and level disparities are most pronounced. Overall, the results highlight the superior performance of the SFANC-NLMS algorithm compared to NLMS and No control conditions, especially under challenging high-noise scenarios. The findings also underscore the critical role of noise level and type in shaping PLN, further

Table 7
Post hoc Tukey HSD results for significant comparisons in the PLN study.

Comparison	p-value	Effect
Moto vs. Street	0.021 *	-2.92
Moto vs. Train	0.00012 ***	-4.66
Street vs. Train	0.24	-1.74285
SFANC-NLMS vs. No Control	< 0.0001 ****	-8.47
SFANC-NLMS vs. NLMS	< 0.0001 ****	-5.11
No Control vs. NLMS	0.002 **	3.37
55 dB vs. 65 dB	< 0.0001 ****	-11.97
55 dB vs. 72 dB	< 0.0001 ****	-22.42
65 dB vs. 72 dB	< 0.0001 ****	-10.45
Moto (55 dB) vs. Moto (72 dB)	< 0.0001 ****	-22.66
Moto (55 dB) vs. Street (72 dB)	< 0.0001 ****	-24.11
Moto (55 dB) vs. Train (72 dB)	< 0.0001 ****	-29.54
Street (55 dB) vs. Train (72 dB)	< 0.0001 ****	-22.77
Train (55 dB) vs. Moto (72 dB)	< 0.0001 ****	-20.37
Train (55 dB) vs. Street (72 dB)	< 0.0001 ****	-21.83
Train (55 dB) vs. Train (72 dB)	< 0.0001 ****	-27.26
SFANC-NLMS (55 dB) vs. SFANC-NLMS (72 dB)	< 0.0001 ****	-20.88
SFANC-NLMS (55 dB) vs. No Control (72 dB)	< 0.0001 ****	-30.77
SFANC-NLMS (55 dB) vs. NLMS (72 dB)	< 0.0001 ****	-25.92
No Control (55 dB) vs. No Control (72 dB)	< 0.0001 ****	-24.08
NLMS (55 dB) vs. No Control (72 dB)	< 0.0001 ****	-27.15
NLMS (55 dB) vs. NLMS (72 dB)	< 0.0001 ****	-22.31
SFANC-NLMS (55 dB) vs. No Control (72 dB)	< 0.0001 ****	-20.52
SFANC-NLMS (Moto, 55 dB) vs. No Control (Street, 72 dB)	< 0.0001 ****	-32.89
SFANC-NLMS (Moto, 55 dB) vs. No Control (Train, 72 dB)	< 0.0001 ****	-35.09
SFANC-NLMS (Moto, 55 dB) vs. NLMS (Train, 72 dB)	< 0.0001 ****	-33.91
No Control (Moto, 55 dB) vs. No Control (Train, 72 dB)	< 0.0001 ****	-30.43
NLMS (Moto, 55 dB) vs. No Control (Street, 72 dB)	< 0.0001 ****	-30.86
NLMS (Moto, 55 dB) vs. No Control (Train, 72 dB)	< 0.0001 ****	-33.06
NLMS (Moto, 55 dB) vs. NLMS (Train, 72 dB)	< 0.0001 ****	-31.89
SFANC-NLMS (Street, 55 dB) vs. No Control (Train, 72 dB)	< 0.0001 ****	-32.66
SFANC-NLMS (Street, 55 dB) vs. No Control (Train, 72 dB)	< 0.0001 ****	-29.66

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$.

validating the effectiveness of advanced noise control techniques. Results of the post hoc are findable in Table 7.

5. Discussion

The following discussion seeks to address the research questions established in Section 1. Section 5.1 examines the impact of ANC on perceived annoyance under different conditions (RQ1). Section 5.2 evaluates the influence of noise level on perceived annoyance under different ANC conditions (RQ2). Finally, Section 5.3 explores the interaction between noise type, ANC condition, and noise level (RQ3).

5.1. Effect of ANC algorithms on perceived annoyance

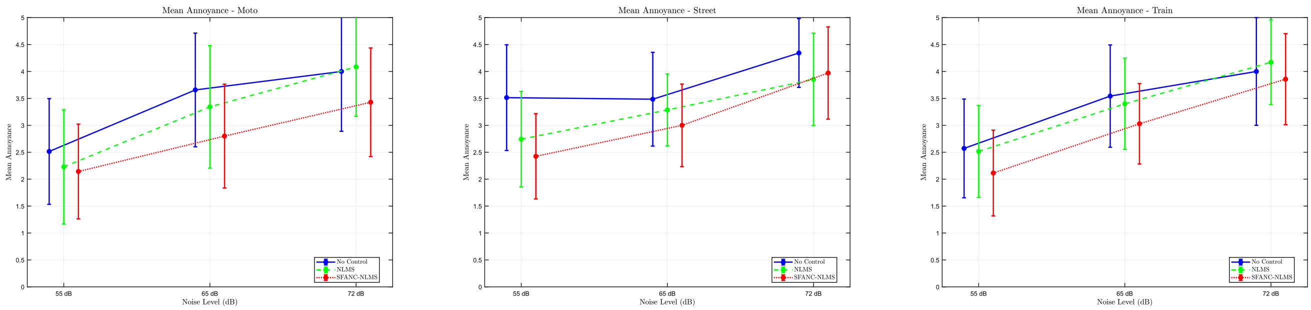
The results of this study provide insights into how different ANC algorithms (NLMS and SFANC-NLMS) influence perceived annoyance in a simulated vehicle environment, addressing RQ1. Overall, the SFANC-NLMS algorithm was more effective in reducing perceived annoyance compared to the traditional NLMS algorithm, across almost all noise types and levels. This was particularly evident for train and motorbike noises, where SFANC-NLMS significantly reduced perceived annoyance. For motorbike noise, SFANC-NLMS also outperformed NLMS, highlighting its ability to manage more complex noise characteristics. While both algorithms showed similar performance in some cases, SFANC-NLMS consistently resulted in lower annoyance scores, suggesting that it is better suited for handling various noise types. Noise level also played a crucial role, with higher levels (72 dB) leading to greater perceived annoyance, regardless of the ANC condition. Interestingly, the interaction between noise type and ANC algorithm was not significant, indicating that the effects of the algorithms and noise types were more influential individually. As shown in Fig. 6, stimuli controlled by SFANC-NLMS generally resulted in the lowest perceived annoyance scores (PAY), confirming its superior effectiveness.

5.2. Effect of sound level on perceived annoyance under different ANC conditions

The results regarding perceived annoyance also reveal that sound level (55, 65, and 72 dB(A)) moderates the relationship between ANC algorithm type and perceived annoyance, addressing RQ2. In general, higher sound levels were associated with higher perceived annoyance scores, even with the application of ANC. This emphasizes the importance of controlling sound intensity to reduce annoyance. The moderating effect of sound level seemed most pronounced at 72 dB, where the differences between algorithms were most evident. However, the interaction between ANC algorithm and sound level did not significantly alter the direction of the relationship between these variables and perceived annoyance. In summary, sound level affects annoyance, but its impact remains consistent across different ANC algorithms.

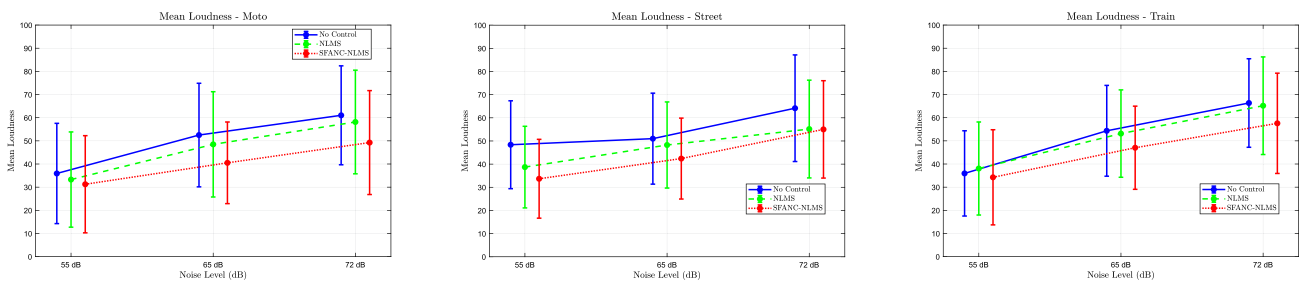
5.3. Interaction between noise sources, ANC condition, and sound levels

Regarding the interaction between noise sources, ANC algorithms, and sound levels, the results show that different noise sources (e.g., motorcycle, street, train noises) interact with ANC algorithms and sound levels to shape perceived annoyance, addressing RQ3. In particular, street and train noises showed a stronger interaction with ANC algorithms, with SFANC-NLMS significantly reducing perceived annoyance compared to NLMS. For motorcycle noise, while SFANC-NLMS also showed greater reductions in annoyance, the interaction between noise type and ANC algorithm was not significant in all cases. This suggests that, while ANC algorithms play a key role in managing different noise



(a) (b) (c)

Fig. 6. Means and standard deviations of the PAY score obtained for different noise levels for (a) Motorbike noise, (b) Street noise, and (c) Train noise.



(a) (b) (c)

Fig. 7. Means and standard deviations of the PLN score obtained for different noise levels for (a) Motorbike noise, (b) Street noise, and (c) Train noise.

sources, the spectral characteristics of the noise have a stronger influence on the algorithm's effect on perceived annoyance. Sound level also had a significant impact, with higher noise levels leading to greater perceived annoyance, regardless of the ANC algorithm or noise type. Additionally, Fig. 7 provides a visualization of the variation in perceived loudness (PLN) scores across different noise types and sound levels, complementing our findings on annoyance perception. As shown in the figure, stimuli controlled by SFANC-NLMS generally resulted in the lowest PLN mean scores, further supporting the conclusion that SFANC-NLMS provides a more comfortable acoustic environment by reducing both annoyance and loudness.

6. Conclusion

This study assessed the impact of different ANC algorithms on perceived annoyance, loudness, and affective quality.

RQ1: To what extent do different ANC algorithms influence perceived annoyance? The results show that the SFANC-NLMS algorithm is more effective than the traditional NLMS algorithm in reducing perceived annoyance, particularly for complex noise sources such as motorbike and train noises.

RQ2: Does sound level moderate the relationship between ANC algorithm and perceived annoyance? Sound level significantly influences perceived annoyance, with higher noise levels (72 dB) leading to greater annoyance, regardless of the ANC condition. However, the effect of sound level did not alter the relationship between ANC algorithm type and perceived annoyance.

RQ3: How do different noise sources interact with ANC algorithms and sound levels to shape perceived annoyance? Different noise sources interacted with ANC algorithms and sound levels, with SFANC-NLMS consistently reducing perceived annoyance more effectively than NLMS across all noise types. Street and train noises showed stronger interactions with ANC algorithms, while the motorbike noise exhibited more complexity.

In conclusion, while objective metrics have already demonstrated the superior performance of the SFANC-NLMS algorithm, this study confirms its effectiveness from a subjective perspective, showing its ability to reduce perceived annoyance and loudness and enhance acoustic comfort. However, noise level remains a key factor influencing subjective experience, emphasizing the need for sound intensity control. Further research is required to optimize SFANC-NLMS for more complex noise profiles and assess its applicability in real-world conditions.

CRediT authorship contribution statement

Alkahf Aboutiman: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Zulfi Rachman:** Writing – review & editing, Validation, Resources, Formal analysis, Data curation, Conceptualization. **Tin Oberman:** Writing – review & editing, Validation, Supervision, Resources, Formal analysis, Data curation, Conceptualization. **Francesco Alletta:** Writing – review & editing, Validation, Supervision, Resources, Formal analysis, Data curation, Conceptualization. **Jian Kang:** Writing – review & editing, Validation, Supervision, Conceptualization. **Hamid Reza Karimi:** Writing – review & editing, Validation, Supervision, Conceptualization. **Francesco Ripamonti:** Writing – review & editing, Validation, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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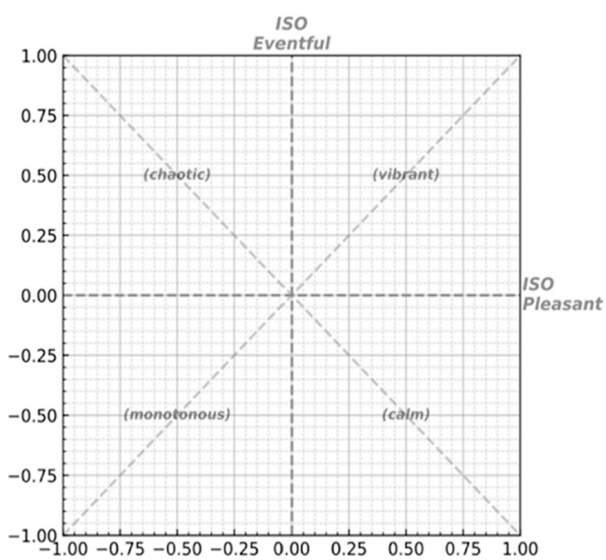
Appendix A. Questionnaires

Table A.1
Pre-test assessment participant information questionnaire.

Question Category	Specific Questions	Rating Scale
Individual Noise Sensitivity (INS)	I am sensitive to noise. I find it difficult to relax in a place that's noisy. I get mad at people who make noise that keeps me from falling asleep or getting work done. I get annoyed when my neighbors are noisy. I get used to most noises without much difficulty.	Totally Disagree–Totally Agree (10-point categorical)
Baseline Noise Annoyance (BNA)	When you are at home, how much does noise from road traffic bother, disturb or annoy you? When you are at home, how much does noise from aircraft bother, disturb or annoy you? When you are at home, how much does noise from train bother, disturb or annoy you? When you are at home, how much does noise from children bother, disturb or annoy you? When you are at home, how much does noise from other people bother, disturb or annoy you? When you are at home, how much does noise from animals bother, disturb or annoy you?	Not at all–Extremely (5-point categorical)
Perceived Stress Scale (PSS-4)	How often have you felt that you were unable to control the important things in your life? How often have you felt confident about your ability to handle your personal problems? How often have you felt that things were going your way? How often have you felt difficulties were piling up so high that you could not overcome them?	Never–Very often (5-point categorical)

Table A.2
Noise Evaluation Questionnaire: PAY, PAQ, and PLN.

Question Category	Specific Questions	Rating Scale
Perceived Annoyance (PAY)	Thinking about the noise you just heard, how much does the noise bother, disturb, or annoy you?	Not at all–Extremely (5-point categorical)
Perceived Affective Quality (PAQ)	Thinking about the sound you just heard, where would you place the surrounding sound environment on this scale?	



Question Category	Specific Questions	Rating Scale
Perceived Loudness (PLN)	How loud would you say the sound environment is?	Scale between 0–100

Data availability

Data will be made available on request.

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