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Auditory alerts for e-scooters: Relationship between pedestrian auditory detection rates and alert sound level

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ABSTRACT

Electric micromobility has the potential to transform the urban transportation system by offering increased personal mobility, whilst reducing congestion and air pollution. Standing electric scooters (e-scooters) are considered as the most popular mode of electric micromobility on our streets today and have seen a significant rise in numbers in recent years, both as part of the shared-use paradigm and through private ownership. However, safety concerns have proved a barrier to public acceptance, with one key safety concern being that e-scooters emit very low noise levels, resulting in a higher perceived level of risk by pedestrians. The issue of electric vehicle audibility is well studied within the context of electric cars and regulations are now in place that stipulate minimum sound levels for electric vehicles (EVs). To achieve these minimum sound levels, Acoustic Vehicle Alerting Systems (AVAS) are used, which provide increased audibility for pedestrians at low speeds. Currently, there are no regulations for micromobility AVAS and research into this topic is limited. In this paper, we consider the development of an e-scooter AVAS by investigating auditory detection rates of e-scooter alert sounds as a function of alert sound level, environmental noise level and distance. A listening experiment was conducted whereby participants were required to identify AVAS signals within a simplified environmental noise spectrum, presented in a randomised yes-no procedure, for a range of e-scooter AVAS conditions and environmental noise levels. Psychometric functions were subsequently derived, resulting in an understanding of auditory detection probabilities as a function of AVAS level, environmental noise level and distance. The presented results are an important step in the understanding of e-scooter safety measures and help establish minimum sound levels for e-scooter AVAS going forward.

1. Introduction

Due to technical advancements and the need for society to move towards low emission transportation, the electric micromobility sector has witnessed a rise in popularity in recent years [1]. Electric micromobility has the potential to offer substantial benefits, such as a decrease in air pollution and enhanced personal mobility. Electric scooters (e-scooters) and electric bikes (e-bikes) are examples of micromobility modes that might significantly reduce traffic congestion, create an environmentally friendly transportation system, provide affordable personal transportation, and improve accessibility [2]. Another advantage of electric micromobility is that electric drivetrains typically generate reduced noise levels in comparison to internal combustion engine vehicles (ICEVs) [3], thereby offering the potential of reduced noise pollution in urban environments. As a consequence, e-scooter usage figures have seen a significant increase in Europe in recent years, with a rise from 360,000 in 2021 to 520,000 shared e-scooters in 2022 [4,5].

Despite the potential benefits of a transportation ecosystem that includes electric micromobility, there are still challenges to address. A study conducted by the UK Department for Transport revealed that 53% of respondents cited safety concerns as a drawback of e-scooters [6] and a comprehensive study on perceptions of an e-scooter trial in Greater Manchester revealed that 45% of respondents had felt unsafe when walking as a result of an e-scooter rider [7]. Moreover, according to UK Government national statistics on e-scooter-related traffic collisions, there has been a significant increase in casualties, with 1,359 reported in 2021 compared to 484 in 2020 [8]. These statistics are based on the UK Government's definition of an 'e-scooter', which dif-

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ferentiates them from other two-wheeled electric vehicles by specifying a top speed limit of 12.5 mph (20 km/h), a maximum weight of 35 kg, and the requirement to accommodate one standing person without seating [9].

Due to the aforementioned lower noise levels of electric drivetrains compared to ICEVs, the uptake of electric micromobility modes and electric vehicles (EVs) has raised safety concerns for pedestrian safety, especially for individuals who are blind or partially sighted. A range of research has been conducted on this topic for over ten years, focusing on EVs [3,10–13], with recent attention given to micromobility [14]. One study highlighted that the risk of road traffic near-misses and accidents involving pedestrians was around 25% more likely when comparing EVs with no alert sounds to ICEVs due to their inherently lower noise levels [15]. Similarly, in the context of electric micromobility, Walton et al. [14] showed that without additional alert sounds, e-scooters are typically inaudible in typical urban soundscapes.

To address these safety concerns relating to audibility, Acoustic Vehicle Alerting Systems (AVAS) are used. The development of AVAS for EVs followed from early research addressing the safety of blind pedestrians and quieter vehicles [11,12]. Several standards now exist that specify the minimum sound requirements for quiet-running vehicles [16–18], such as UNECE Regulation 138. According to this regulation, AVAS sound levels must meet minimum requirements in one-third octave bands ranging from 160 Hz to 5 kHz. Compliance requires meeting the minimum levels in at least two bands, with one band below or at 1600 Hz. The required AVAS operation speed typically extends up to 20 km/h, as above this speed the dominance of rolling and aerodynamic noise leads to a negligible difference in noise levels between EVs and ICEVs [3]. Additionally, AVAS must vary proportionally with speed, increasing by an average of at least 0.8% per 1 km/h within the range of 5 km/h to 20 km/h [16].

Whilst current AVAS regulations for quiet running vehicles specify minimum levels within one-third octave frequency bands, there is still scope for a wide range of AVAS sounds to be designed. It is desirable that AVAS sounds i) be sufficiently detectable for pedestrians above typical soundscapes, ii) should not cause undue noise pollution and annoyance within the environment, iii) should ideally not detract from the overall product experience, iv) should reflect the operational state of the vehicle, including speed, location and acceleration, and, v) align with product branding of the vehicle manufacturer / operator.

Balancing detectability and acceptability is of key interest when designing AVAS sounds, and indeed a range of previous studies have investigated detectability and annoyance of specific AVAS sound characteristics [14,19–24]. Parizet et al. [19] sought to create alerting sounds that were easily audible, whilst limiting annoyance, as part of the eVADER project (electric Vehicle alarm for Detection and Emergency Response). Numerous parameters were used to create the sounds, such as the number of harmonics, the amplitude modulation (AM), and the frequency modulation (FM), and the efficiency of each was assessed using a detection task in a simulated pass-by scenario. It was discovered that the alert sounds with the fewest harmonics, without FM, and with prominent and erratic AM had the quickest reaction times. High degrees of detectability were found to be connected with high levels of unpleasantness in an extension of this study [20] that looked at how the efficiency of each alert sound was related to its perceived unpleasantness. In addition to taking the masking effect of background noise into account, Lee et al. [22] also addressed the trade-off between detectability and acceptance for AVAS sounds. Amplitude modulated signals, as in [19], offered the best results in terms of annoyance and detectability.

Walton et al. [14] explored the performance of AVAS characteristics in the context of e-scooter detection and annoyance. Simulations of e-scooter passes were presented over a three-dimensional loudspeaker array and reaction times and annoyance ratings were gathered. By plotting detection distance versus annoyance, stimuli could be evaluated within a perceptual space so as to optimise detectability and annoyance. Whilst detectability and annoyance were seen to be highly correlated, a cluster of stimuli offered good detectability with relatively low annoyance ratings. These sounds were characterised by sine tones with components of 400, 600 and 800 Hz, and with amplitude modulation. Furthermore, an impulsive 1 kHz tone at a rate of 7 Hz was also seen to be effective. This suggests that modulated or impulsive tones with frequency content in the 800 Hz - 1 kHz range, and with sine type characteristics, may provide optimal micromobility AVAS sounds.

Whilst identifying appropriate sound characteristics is crucial for optimising AVAS detectability and annoyance, so is identifying appropriate emission levels. Hsieh et al. [25] investigated auditory thresholds for low-, medium-, and high-frequency AVAS sounds for EVs, by means of a “yes-no” forced choice auditory detection experiment. Here, the low- mid- and high- frequency AVAS sounds were in the ranges 160 - 1250 Hz, 315 - 2500 Hz, and 630 - 5000 Hz respectively. The independent variables of AVAS sound, AVAS level, environmental noise level and distance were investigated and detection probabilities were subsequently calculated by means of logistic regression analysis. Out of the AVAS sounds tested, the high frequency sound offered increased detectability and the detection rate of a 51 dBA AVAS sound (15.3%) was significantly higher than that of a 46 dBA sound (6.7%) for the high frequency condition, when averaged across the other variables. It was reported, however, that rates of detection were less than 20% for all experimental conditions.

In the case of electric micromobility, it could be argued that specifying an appropriate AVAS emission level is even more important than for EVs, as there is no structure to provide sound insulation between AVAS loudspeaker and vehicle user. So as to increase acceptability for micromobility users, it is paramount to specify the lowest AVAS sound necessary to sufficiently alert pedestrians in a given context. To achieve this, an understanding of detection probability is required, for a range of AVAS sounds, AVAS levels, environmental noise levels and pedestrian distance. The objective of this paper is to investigate the detectability of a series of e-scooter alerting sounds as a function of these variables. Whilst previous research has focused on detection probabilities for EV AVAS sounds spanning low, medium and high frequency characteristics, the present paper focuses on micromobility AVAS sounds (including associated baseline noise profiles) spanning continuous, impulsive and mixed characteristics (i.e. a combination of both continuous and impulsive characteristics). To achieve this, a listening experiment has been conducted whereby participants were required to identify AVAS signals within a simplified environmental noise spectrum, presented in a randomised yes-no procedure, for a range of e-scooter AVAS conditions, environmental noise levels and distances. Psychometric functions were subsequently derived, resulting in an understanding of auditory detection probabilities as a function of AVAS level, environmental noise level and distance.

2. Methods

The listening experiment presented in this paper was conducted as a laboratory-based study within a dedicated listening room at The University of Salford. Participants were required to listen to stimuli over headphones, which consisted of target signals (AVAS sounds) in the presence of masking environmental noise. After each stimuli presentation, participants were required to make a binary yes-no response on whether they heard the target signal within the noise. The independent variables studied were $AVAS_{type}$, $AVAS_{level}$, environmental noise level (*Environment*) and distance from e-scooter (*Distance*), as further introduced in the following sections.

2.1. Ethical approval

Prior to conducting the subjective experiment, the following procedure and design was approved by the Ethics Committee of the University of Salford, UK. Informed consent was obtained from all participants

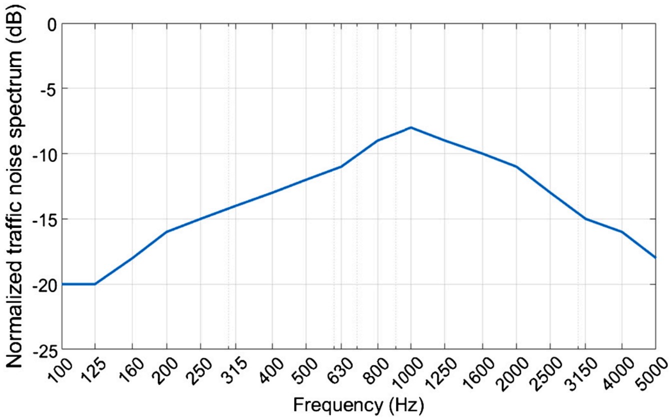


Fig. 1. Normalized road traffic noise spectrum as reported in BS EN 1793-3 [29].

involved in the study and all methods were carried out in accordance with relevant guidelines and regulations.

2.2. Experimental design

The listening experiment utilised a "yes-no" method, which is a popular paradigm in auditory signal detection experiments [26,27]. Within the "yes-no" procedure, each trial corresponds to a single target signal within the presence of background noise. After each signal presentation, participants are required to respond by selecting either *yes* or *no*, depending upon if they detected the target signal.

The user interface was implemented with the HULTI-GEN listening test interface generator [28], which uses the Cycling '74 MAX/MSP software package. Each participant completed a total of 108 yes-no ratings, split into 3 stimuli groups of 36, which included combinations of the variables $AVAS_{level}$, Environment and Distance for each $AVAS_{type}$. There was an optional short break between each stimuli group. Upon selecting *Play*, a 5 second sample of environmental noise commenced playback, with a target AVAS signal present for the final 3 seconds of each sample, including a 10 ms fade-in and fade-out. Participants were then asked *"Was there an alert sound present?"*, with *Yes* and *No* buttons available.

The independent variables studied were $AVAS_{type}$ (S_{cont}, S_{mix}, S_{imp}), $AVAS_{level}$ (56, 58, 60, 62, 64, 66 dB L_{AFmax} at 2 m), Environment (50, 55, 60 dB L_{Aeq}) and Distance between e-scooter and pedestrian (5, 10 m). Each stimuli group of 36 trials consisted of a single $AVAS_{type}$ with all combinations of other variables. The order of stimuli groups was balanced across participants and all stimuli within each group was randomised. A short training section was presented prior to the main experiment, whereby participants completed a small number of detection tasks for each $AVAS_{type}$, so that participants were familiar with the procedure and with each sound.

2.3. Environmental noise

A simplified environmental noise spectrum was used as a masker during the experiment, as based on the normalised traffic noise spectrum as specified in the standard BS EN 1793-3 [29]. By using a simplified urban noise spectrum, more robust and consistent detectability threshold data can be achieved, in comparison to using audio recordings of urban soundscapes, which are typically more time-varying in nature. The synthesised road traffic noise spectrum was implemented via filtered pink noise to achieve the spectrum presented in Fig. 1. This spectrum was then calibrated to overall broadband levels of 50 dB, 55 dB, and 60 dB L_{Aeq}, which represent a range of typical urban noise levels.

Table 1
Sound quality metrics of fluctuation strength and impulsiveness for the AVAS sounds used within the experiment.

AVAS	Fluctuation Strength (vacil)	Impulsiveness (IU)
Continuous	0.07	0.35
Impulsive	1.76	1.13
Mixed	0.06	0.32

2.4. Stimuli

2.4.1. AVAS sound design

Previous research has highlighted a range of considerations for AVAS sound design, including accounting for human frequency sensitivity [30] which peaks between 1 kHz and 5 kHz, accommodating individuals with high frequency hearing loss by including components lower than 1 kHz [30], and avoiding components lower than 200 Hz so as to limit unwanted noise propagation over long distances and intrusion through typical building envelopes [31]. AVAS sounds with prominent amplitude modulation and a small number of harmonics have been shown to optimise detectability and annoyance [19]. With regards to temporal characteristics, both *impulsive* and *continuous* type AVAS sounds have been shown to offer good detectability performance [14].

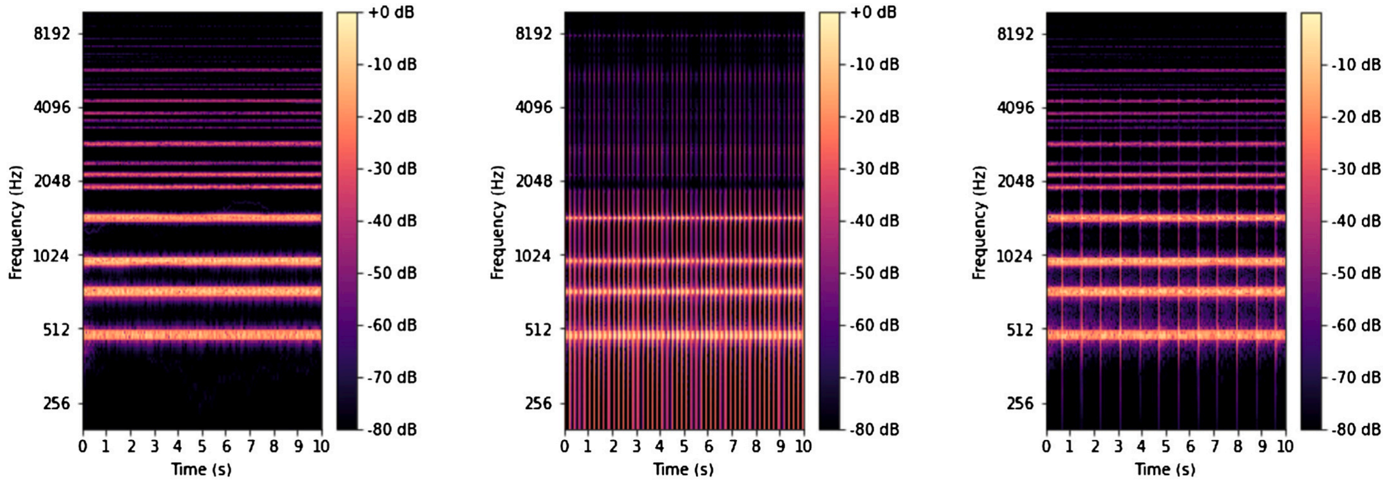
In this study, 3 AVAS sounds ($AVAS_{type}$) were tested with the specific objective of comparing detectability performance of *impulsive* and *continuous* type AVAS sounds. In terms of perception, impulsive sounds are characterised by a series of short, repeated impulses with a rapid attack and delay, whereas continuous sounds refer to those which are perceived as a *chord* and have no perceivable attack. The three AVAS sounds were generated using software synthesizers within a digital audio workstation and are based around the key considerations for AVAS design as discussed above. Further details are outlined below and spectrograms are presented in Fig. 2:

- S_{cont} - Continuous AVAS sound based around frequency components of 478 Hz, 728 Hz, 956 Hz and 1433 Hz, and an amplitude modulation rate of 4.9 Hz.
- S_{imp} - Impulsive AVAS sound based around frequency components of 478 Hz, 716 Hz, 957 Hz and 1434 Hz, and an impulse rate of 4.9 Hz.
- S_{mix} - Combined continuous and impulsive AVAS sound using S_{cont} and an impulsive element, with the same frequency components as above, and an impulse rate of 1.15 Hz.

2.4.2. Sound quality metrics

To objectively quantify the differences between the AVAS sounds, the Sound Quality Metrics (SQMs) of fluctuation strength (vacil) and impulsiveness (IU) were calculated using HEAD Acoustics ArtemiS Suite 12.5 software, as based on the hearing model given by Sottek [32]. Fluctuation strength quantifies subjective perception of amplitude modulation of a sound up to approximately 25 Hz, with peak values corresponding to modulation at 4 Hz. Impulsiveness is a measure of the perception of rapid and large signal level fluctuations, with values increasing up to an impulse rate of approximately 10 Hz. As well as being related to impulse rate, impulsiveness is related to impulse exaggeration, impulse width and impulse function slope. Prior to the SQM calculations, the AVAS sounds were processed with the auralisation procedure at a pedestrian to e-scooter distance of 5 m (refer to the following section) and therefore also included the baseline e-scooter noise profile.

As presented in Table 1, the fluctuation strength and impulsiveness values for AVAS sound S_{imp} are notably higher than for S_{mix} and S_{cont}, as expected due to the nature of the sound. The SQM values for S_{cont} and



(a) (b) (c)

Fig. 2. Spectrograms for AVAS stimuli S_{cont} (a), S_{imp} (b) and S_{mix} (c). Colour represents relative amplitude in decibels, y-axis represents frequency (Hz), and x-axis represents time (s). The spectrograms were computed with the Librosa STFT Python package, with a window size of 1024, a hop length of 512 and a raised cosine window ('hann').

S_{mix} are similar and this is likely due to the low impulse rate related to S_{mix} (1.15 Hz), which is below the peak frequencies for both fluctuation strength and impulsiveness.

2.4.3. E-scooter AVAS auralisation

In order to accurately present the e-scooter AVAS sounds, an auralisation procedure was implemented in the software Unity which accounted for AVAS loudspeaker acoustical directivity, ground reflections, air absorption, and spatial hearing through binaural reproduction.

An overview of the calibration process for the e-scooter auralisation is as follows. Firstly, an e-scooter baseline audio recording (without AVAS) was calibrated to a level of 52 dB L_{AFmax} at 2 m distance to the side of the listening position, as based on baseline measurements outlined in [14]. This audio recording included contributions from tyre-road interaction noise, electric motor noise and aerodynamic noise. Following this, additional alert sounds of each $AVAS_{type}$ (S_{cont}, S_{mix}, S_{imp}) were calibrated to each $AVAS_{level}$ (56, 58, 60, 62, 64, 66 dB L_{AFmax}), all at 2 m distance from the listener's position. This corresponds to the calibration distance typically used for AVAS measurements, as specified in UNECE Regulation 138 [16]. Each stimulus calibrated at 2 m distance from the listener was then moved to the two Distance levels (5 and 10 m) behind the listening position, see Fig. 3. The stated $AVAS_{level}$ levels therefore correspond to the 2 m calibration distance and not the final 5 m and 10 m auralisation distances. This approach is beneficial as it enables distance to be modelled in the logistic regression as a separate variable, with calibration levels referencing current standard protocols. It should further be noted that 56 dB (L_{AFmax}) was chosen as the minimum $AVAS_{level}$ as this corresponds to the minimum AVAS requirements specified in UNECE Regulation 138 for quiet running vehicles [16].

No additional auralisation processes were applied to the AVAS sounds as no movements during playback were simulated, i.e. the AVAS sounds were kept at the corresponding distances for the duration of the signal. This enabled the calculation of probability of detection distributions with respect to distance and ensured responses were based upon auditory thresholds instead of reaction times. Including e-scooter movements, and therefore reaction times, within a detection task was previously presented [14].

2.5. Apparatus

Audio was presented with Sennheiser HD 650 open-back headphones, with an RME ADI-2 digital to analogue converter and headphone amplifier. Calibration of reproduced audio levels was undertaken using a B&K Type 4128-C Head and Torso Simulator, a Norsonic 336 microphone amplifier, a BSWA 308 sound level meter (class 1), and a B&K 4230 sound level calibrator.

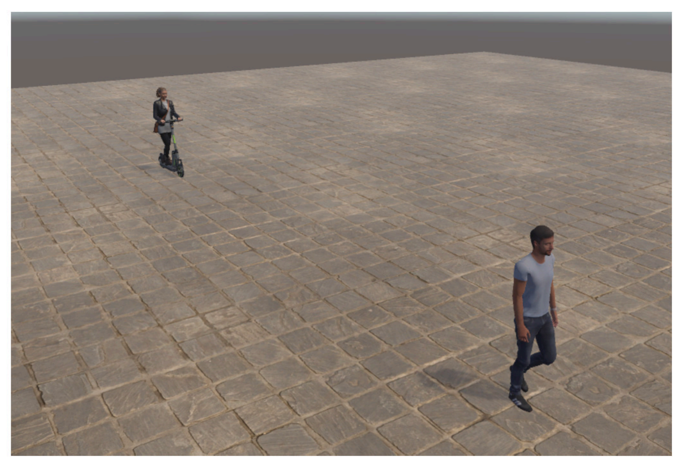


Fig. 3. Visual representation of e-scooter auralisation within Unity. The presented scene here corresponds to the 10 m distance scenario.

2.6. Participants

A total of 27 participants took part in the listening experiment, which included 15 individuals aged between 18 and 24, 8 individuals aged between 25 and 34, 3 individuals aged between 35 and 44, and 1 individual aged between 45 and 54. The group consisted of 22 males and 5 females. All participants were fluent in English and self reported normal hearing. Participants were recruited from a listening experiment participant database and included individuals who were both internal and external to the university. Participants received a small monetary compensation for their participation.

2.7. Statistical analysis

To analyse the data, a Generalized Linear Model (GLM) was conducted using the statistical software SPSS (IBM), with a Binary Logistic response function. The advantage of a GLM approach compared to a typical Binary Logistic Regression, is that a GLM is suited to repeated measures data (i.e. multiple data points from the same participants),

Table 2
Type III model effects calculated with the Wald Chi-square test.

Variable	Wald Chi-Square	df	Sig.
$AVAS_{level}$	367.76	1	.000
Environment	502.73	1	.000
Distance	474.81	1	.000
$AVAS_{type}$	111.29	2	.000

whereas Binary Logistic Regression requires independence of observations.

In logistic regression, the *logit* function is defined as [33]:

$$logit(p) = log\left(\frac{p}{1-p}\right) \tag{1}$$

where p refers to the probability of an event occurring. When expressed as a function of independent variables, this equation reads:

$$logit(p) = a + b_1x_1 + b_2x_2 + b_3x_3 + \ldots \tag{2}$$

where a is the constant (intercept) and b is the coefficient of the predictor variables. The probability, p, can then be expressed as:

$$p = \frac{e^{(a+b_1x_1+b_2x_2+b_3x_3+\ldots)}}{1+e^{(a+b_1x_1+b_2x_2+b_3x_3+\ldots)}}. \tag{3}$$

These equations are subsequently used within the analysis to develop the probability of detection equations.

3. Results and discussion

3.1. Descriptive statistics

A total of 108 variable combinations were evaluated across the independent variables $AVAS_{type}$ (S_{cont}, S_{mix}, S_{imp}), $AVAS_{level}$ (56, 58, 60, 62, 64, 66 dB L_{AFmax}), Environment (50, 55, 60 dB L_{Aeq}) and Distance (5, 10 m). The dependent variable was a dichotomous response (yes / no) for each variable combination. When evaluating the counts of 'yes' and 'no' responses across all conditions, it is seen that 38.4% of responses correspond to negative responses (1120 data points), whilst the remaining 61.6% of responses (1796 data points) correspond to positive responses. This suggests an appropriate range of variables was used for evaluating detection thresholds. To compare responses across participants, the relative ratio of yes/no responses was calculated for each participant and compared to the sample as a whole. No participants were identified as outliers (greater than 1.5 times the interquartile range above the upper quartile), based on an upper adjacent of 79.6%, a Q3 of 71.1%, a median of 64.8%, a Q1 of 51.4% and a lower adjacent of 36.1%. As such, all participants were included within the subsequent analysis.

3.2. Logistic regression

Table 2 presents Wald Chi-squared test results for the covariates $AVAS_{level}$, Environment and Distance, as well as the factor $AVAS_{type}$. These results represent how significant the independent variables are in the generation of the Generalized Linear Model. The results highlight that all independent variables significantly influence the dependent response variable on a $p < .05$ level.

To gain insight into the differences between the levels of the variable $AVAS_{type}$, analyses are conducted for the stimuli S_{cont}, S_{mix} and S_{imp} separately. Table 3 shows the model parameter estimates and associated Wald Chi-square test values for each level of $AVAS_{type}$. As with the results in Table 2, all independent variables contribute significantly to the model for each of the AVAS sounds.

In the context of the parameter estimates presented in Table 3, the probability of detection for the three AVAS types can be expressed as a function of the independent variables $AVAS_{level}$, Environment and Distance with the following equations:

Table 3
Parameter estimates and Type III model effects associated with each level of the variable $AVAS_{type}$.

$AVAS_{type}$	Variable	B	Wald Chi-Square	df	Sig.
S_{cont}	AVAS Level	.175	44.11	1	<.001
	Environment	-.351	162.86	1	.000
	Distance	-.516	147.31	1	.000
	Intercept	12.910	36.08	1	<.001
S_{mix}	AVAS Level	.468	156.99	1	.000
	Environment	-.443	182.14	1	.000
	Distance	-.680	178.29	1	.000
	Intercept	1.584	.612	1	.434
S_{imp}	AVAS Level	.647	150.32	1	.000
	Environment	-.551	155.36	1	.000
	Distance	-.831	142.92	1	.000
	Intercept	-.401	.030	1	.863

$$p[S_{cont}] = \frac{e^{(12.91+0.175AL-0.351E-0.516D)}}{1+e^{(12.91+0.175AL-0.351E-0.516D)}} \tag{4}$$

$$p[S_{mix}] = \frac{e^{(1.584+0.468AL-0.443E-0.680D)}}{1+e^{(1.584+0.468AL-0.443E-0.680D)}} \tag{5}$$

$$p[S_{imp}] = \frac{e^{(-0.401+0.647AL-0.551E-0.831D)}}{1+e^{(-0.401+0.647AL-0.551E-0.831D)}} \tag{6}$$

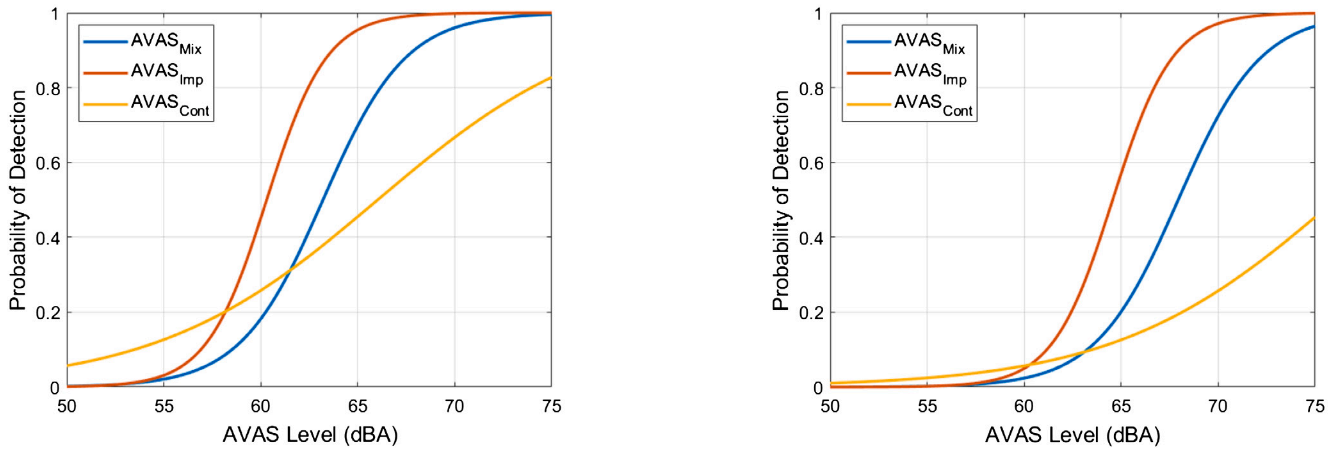
where AL is $AVAS_{level}$ in dB, E is environmental noise level in dB and D is distance in meters. Probability of detection curves can subsequently be generated using these equations, by plotting probability across a range of values, as discussed in the following sections.

3.2.1. Analysis with respect to $AVAS_{level}$

Fig. 4 presents probability of detection curves with respect to $AVAS_{level}$, for two scenarios (i.e. discrete distance and environmental noise levels). Both of these scenarios use a detection distance of 10 m, which can be considered a suitable 'risk threshold' for e-scooters, as based on the minimum stopping distances required for e-scooters on UK roads [34], in addition to knowledge of braking response times for e-scooters [35]. In signal detection theory, the *absolute threshold*, or the lowest level of stimulus that is perceptible, is often defined at a 50% probability of detection level [36]. As such, we can compare the probability of detection curves by considering the 50% detectability level across conditions. It is seen that in a 55 dB L_{Aeq} environment, the 50% detectability threshold corresponds to an $AVAS_{level}$ of 60 dB (L_{AFmax} at 2 m) for S_{imp}, 63 dB (L_{AFmax} at 2 m) for S_{mix} and 66 dB (L_{AFmax} at 2 m) for S_{cont}. In a 60 dB L_{Aeq} environment, the detection thresholds correspond to an $AVAS_{level}$ of 65 dB (L_{AFmax} at 2 m) for S_{imp}, 68 dB (L_{AFmax} at 2 m) for S_{mix} and 76 dB (L_{AFmax} at 2 m) for S_{cont}. These results highlight that an impulsive type AVAS sound can lead to an improved detectability in comparison to a continuous type AVAS sound, with a greater difference in detectability for louder environmental noise conditions. When averaging across $AVAS_{type}$, an $AVAS_{level}$ of 62 dB (L_{AFmax} at 2 m) corresponds to the detection threshold in a 55 dB L_{Aeq} environment, whereas an $AVAS_{level}$ of 68 dB (L_{AFmax} at 2 m) corresponds to the detection threshold in a 60 dB L_{Aeq} environment.

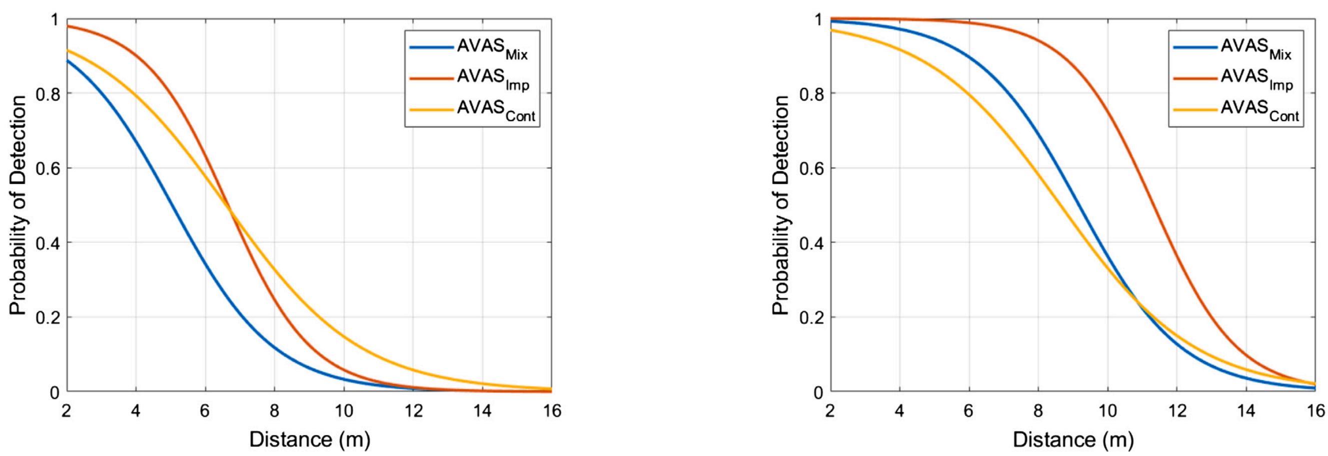
3.2.2. Analysis with respect to distance

Fig. 5 presents probability of detection curves with respect to Distance, for two scenarios. In the first, an $AVAS_{level}$ of 56 dB L_{AFmax} is used within a 55 dB L_{Aeq} environment. This corresponds to the minimum AVAS requirements specified in UNECE Regulation 138 for quiet running vehicles [16]. In this case, the 50% threshold is achieved when at a distance of 5 m to 6.6 m from the listener, dependent upon $AVAS_{type}$. When at 10 m distance, the probability of detection is less than 20% for all AVAS types. In the case of a 62 dB L_{AFmax} $AVAS_{level}$,



(a) D = 10 m, E = 55 dB L_{Aeq} (b) D = 10 m, E = 60 dB L_{Aeq}

Fig. 4. Probability of detection distributions with respect to AVAS$_{level}$, where D is variable Distance and E is variable Environment.



(a) AL = 56 dB L_{AFmax} at 2 m, E = 55 dB L_{Aeq} (b) AL = 62 dB L_{AFmax} at 2 m, E = 55 dB L_{Aeq}

Fig. 5. Probability of detection distributions with respect to Distance, where AL is variable AVAS$_{level}$ and E is variable Environment.

the 50% threshold increases to approximately 10 m, as previously discussed. When at 5 m distance, the probability of detection increases to over 90% for all AVAS types.

3.2.3. Analysis with respect to environment

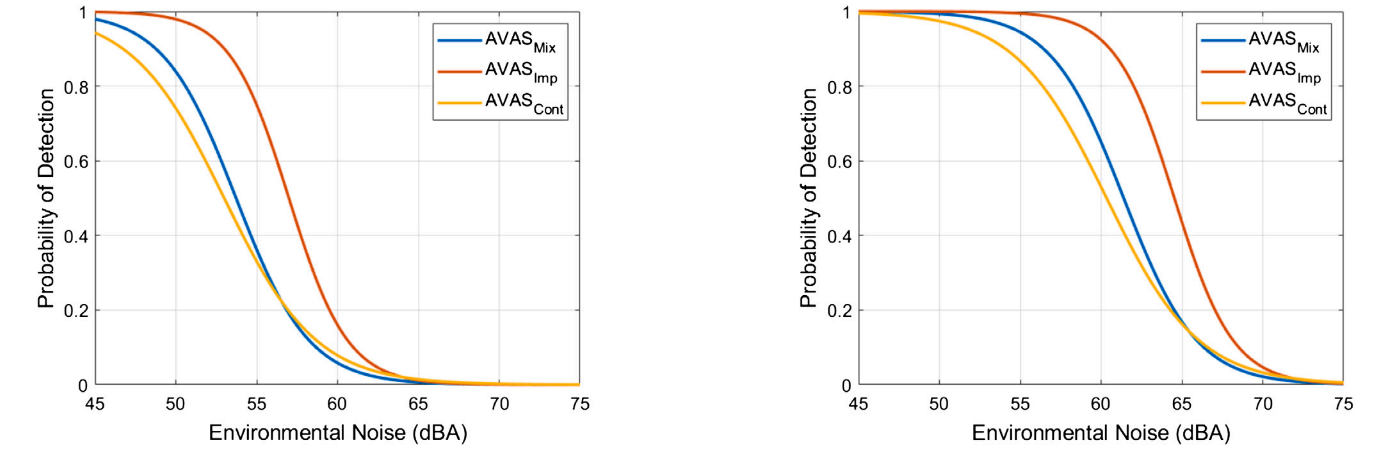
Fig. 6 presents probability of detection curves with respect to Environment, for two scenarios. At 10 m distance and an AVAS$_{level}$ of 62 dB L_{AFmax} (as based on results from Section 3.2.1), probability of detection is seen to trend from approximately 1 in a 45 dB L_{Aeq} environment, to approximately 0 in a 65 dB L_{Aeq} environment. In a 55 dB L_{Aeq} environment, the detection probabilities correspond to those presented in Fig. 4. When a distance of 5 m is used in conjunction with a 62 dB L_{AFmax} AVAS$_{level}$, the probability curves are shifted to higher environmental noise levels by approximately 6 dB. This is expected considering acoustic propagation theory, which states that for a doubling of distance, the sound pressure of a source reduces by 6 dB.

3.3. Linear regression analysis

In addition to the GLM analysis with a Binary Logistic response function as detailed above, a supplementary linear regression analysis was conducted. The previous sections identified that the impulsive AVAS sound is typically more detectable than the mixed and continuous type AVAS sounds. The aim of this section is to quantify this difference across the presented conditions.

To achieve this, the mean detection rate for each AVAS$_{level}$ and Environment combination (averaged across participants) was compared to the *prominence* of each condition, see Fig. 7. Here, prominence refers to the difference between the AVAS level and environmental noise level and is calculated by subtracting the environmental noise level in dB L_{Aeq} from the AVAS$_{level}$ in dB L_{AFmax}. The data shown is for the 10 m Distance condition and responses of 0% and 100% detection rate are excluded to allow for fitting with linear models. Linear regression relations were subsequently derived for each AVAS$_{type}$. To allow for a more meaningful comparison, the same regression slope was used across groups and this was calculated as the mean of the three individual slopes. A similar approach has been taken for the comparison of the annoyance of unmanned aerial vehicles and road traffic vehicles [37].

By comparing the slopes in Fig. 7, it can be concluded that the impulsive sound S$_{imp}$ has an improved detectability of 2.94 dB when compared to S$_{cont}$ and an improved detectability of 2.50 dB when compared to S$_{mix}$. In other words, for equal detectability, AVAS sound S$_{cont}$ would need to be 2.94 dB louder than S$_{imp}$ for a given prominence. The difference between S$_{mix}$ and S$_{cont}$ is seen to be much smaller at 0.44 dB. These results align with the sound quality metrics presented in Section 2.4.2 where it was seen that the fluctuation strength and impulsiveness values for S$_{imp}$ were much greater than those of S$_{mix}$ and S$_{cont}$, which were more similar. This data indicates that the sound quality metrics of fluctuation strength and impulsiveness could be used to predict detectability performance of AVAS sounds, which complements existing research on the topic showing that sound quality metrics can



(a) D = 10 m, AL = 62 dB L_{AFmax} at 2 m. (b) D = 5 m, AL = 62 dB L_{AFmax} at 2 m.

Fig. 6. Probability of detection distributions with respect to Environment, where D is variable Distance and AL is variable $AVAS_{level}$.

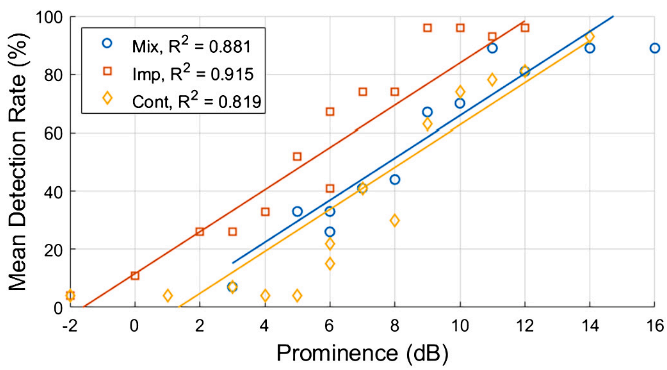


Fig. 7. Linear regression results when considering mean detection rate versus prominence. Equal slopes are used across $AVAS_{type}$ groups to compare offset. Prominence refers to difference between $AVAS_{level}$ and the environmental noise level. Response data is for 10 m distance condition and each data point is averaged data across all participants.

be useful for predicting subjective annoyance for AVAS sounds [14]. However, further work is needed to explore this relationship in more detail.

4. Summary and conclusions

By means of a detection threshold listening experiment and subsequent binary logistic regression analysis, an understanding of how e-scooter AVAS detectability relates to AVAS characteristics, AVAS level, environmental noise level and detection distance has been gained. All of the studied independent variables were seen to significantly contribute to the Generalized Linear Model with a Binary Logistic response function and equations for the probability of detection for each $AVAS_{level}$ were subsequently developed.

When comparing AVAS sounds with impulsive, continuous and mixed characteristics, it was observed that impulsive components can aid in detectability, with a detectability improvement of approximately 3 dB when comparing an impulsive AVAS sound and a continuous AVAS sound of similar frequency components. This is consistent with general understanding of auditory perception, with an example being the 'Rating Penalty' which is applied to environmental noise impact assessments [38], which penalises impulsive sounds due to their increased noticeability and annoyance. Indeed, the effectiveness of impulsive type sounds for detectability is observed in auditory alerts and alarms throughout the built-environment and product design. A consideration of impulsive type AVAS sounds is the potential for increased annoyance for pedestrians and users, as discussed in [14], and therefore a trade off between detectability and annoyance may need to be made depending upon the context of use.

By obtaining response data for different values of $AVAS_{level}$, probability of detection could be plotted against $AVAS_{level}$ for different environments. When analysing insights regarding AVAS emission level, it is important to also consider the environmental noise level, as the masking effect of the environmental noise influences detectability of the AVAS sound. Whilst urban environments have a range of environmental noise levels, a typical average level could be considered to be 55 dB L_{Aeq}, as based on the EU threshold for excess exposure defined in the Environmental Noise Directive, which indicates an annual average level during the day, evening and night [39]. For a 55 dB L_{Aeq} environment, a 56 dB (L_{AFmax} at 2 m) AVAS sound has a 50% chance of detectability when within a distance of 5-7 m of a pedestrian. When considering this in relation to the minimum stopping distances required for e-scooters on UK roads of 7.5 m [34], this detectability performance is seen to be insufficient for e-scooters, especially when considering braking response times [35]. The minimum AVAS levels of 56 dB L_{AFmax} specified in UNECE Regulation 138 [16] are therefore unsuitable for e-scooter AVAS implementations, if a timely detection is desired. When averaging across $AVAS_{type}$, an $AVAS_{level}$ of 62 dB (L_{AFmax} at 2 m) corresponds to a 10 m detection distance in a 55 dB L_{Aeq} environment, suggesting that such an AVAS level may be more appropriate for micromobility.

So as to optimise detectability and annoyance in a wide range of environments, adaptive AVAS systems should be sought, which adjust the AVAS emission level with respect to the environmental noise level. The equations developed in this paper could help determine the relationship between these two variables, as based on a target probability of detection. The differences in AVAS emission level necessary for an equivalent detectability vary significantly across typical urban soundscapes. For example, in a 45 dB L_{Aeq} environment, an absolute threshold at 10 m is achieved with an AVAS level of 52 dB L_{AFmax}, whereas in a 65 dB L_{Aeq} environment, a 73 dB L_{AFmax} AVAS sound would be necessary. This large disparity between required levels highlights the difficulties in designing an AVAS which does not adapt to the environmental noise conditions. Further work should therefore focus on designing adaptive AVAS for micromobility, as benefits could be achieved for both pedestrian safety and limiting noise pollution.

To conclude, the results in this paper represent an important step in the understanding of e-scooter safety measures and are a useful reference for micromobility AVAS guidelines going forward. Through the psychometric functions developed here, relationships between probability of detection and AVAS characteristics, AVAS level, environmental noise level and perception distance have been investigated. The regression equations presented provide valuable and actionable insights into AVAS perception, which can be utilised by other researchers, industry and policy makers. Ultimately, this research contributes to the wider deployment of micromobility in a safe manner, which could help solve some of the transportation issues our urban areas are facing today. Going forward, this study could be extended to further investigate the influence of AVAS frequency content, modulation rate and ratio between continuous and impulsive AVAS components to gain a more holistic understanding of acoustic alerts for micromobility and quiet running transportation as a whole.

CRediT authorship contribution statement

Conceptualization, T.W. and A.J.T.; methodology, T.W., A.J.T. and D.S.E.; formal analysis, T.W.; data curation, D.S.E. and T.W.; writing—original draft preparation, T.W., D.S.E. and A.J.T.; writing—review and editing, A.J.T. and T.W.; visualization, T.W.; supervision, A.J.T. and T.W.; funding acquisition, A.J.T. All authors have read and agreed to the published version of the manuscript.

Declaration of competing interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Data availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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