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Detection of Sound from AVAS in Urban Environments

Master's thesis in Sound and Vibration Programme

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DEPARTMENT OF ARCHITECTURE AND CIVIL ENGINEERING
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Abstract

Functionality of AVAS (Acoustic Vehicle Alert System) faces challenges in urban environments, where background noises may mask AVAS sounds. From a safety perspective, designing AVAS sounds that effectively warn vulnerable road users (without causing extensive environmental noise) is even more crucial in heavy vehicles since they have longer braking distances, greater momentum, and more blind spots than light vehicles. This study aims to contribute to the safety aspects of battery electric trucks (BEV trucks) by exploring their detectability in urban areas and their classification rate, which shows whether they can be distinguishable from cars.

In this regard, listening tests were conducted with 51 participants: eight distinct vehicle sounds, five of which belong to a BEV heavy truck, one to an ICE (Internal combustion engine) truck, one to a BEV passenger car, and one to an ICE passenger car. Each vehicle sound was presented both at 10 and 20 km/h. In the first session of the test, participants were tasked with classifying approaching vehicles as either trucks or cars, without additional urban background noise (the equivalent levels are about 45 dB(A)). During the second session, they were tasked with detecting approaching vehicles amidst continuous urban background noise (the equivalent levels are in the range between 57 and 62 dB(A)) and then classifying the detected ones.

The results revealed that in the first session of the test, where there was no additional background noise, 50% of the vehicles were correctly classified within the safe zone. The vast majority of the vehicles approaching at 10 km/h were classified within the safe zone, while those approaching at 20 km/h were classified within the unsafe zone. In the second session, with continuous urban background noise, 30% of the vehicles were detected and then correctly classified within safe distances. Unlike the first session, a large portion of the vehicles approaching at 20 km/h were detected and then correctly classified within the safe zone, while those approaching at 10 km/h were detected and then classified within the unsafe zone. While the ICE truck outperformed at both speeds and in both sessions, the accuracy of the BEV truck results varied depending on the session and vehicle speed. Moreover, the accuracy rates of the tasks' results were mainly affected by whether the AVAS sound was in active mode or not, the modulation of the AVAS sound, and whether the tonal components of the BEV truck were dominant or not. These findings may provide insights into the current and future needs of designing AVAS sounds for electrified trucks.

Keywords: Acoustic Vehicle Alerting Systems, Electric Heavy Vehicles, BEV Trucks, Exterior Vehicle Sound, Pedestrian Safety, Detectability, Listening Experiments.

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Special thanks go to all the participants in the listening tests; their contributions were crucial to this study.

On a personal note, to my family and friends, it is great to know you are always there. Lastly, Halil, canım, this study is dedicated to the orchid—following the lemon tree, keep an eye out for the next one!

Bircan, Stockholm, 2024

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Introduction

1.1 Problem Statement

Electric vehicles can pose a road safety hazard to vulnerable road users (VRUs): pedestrians are twice as likely to be hit by an electric or hybrid-electric car than an internal combustion engine car (Edwards et al., 2024).

Although Acoustic Vehicle Alerting System (AVAS) helps prevent accidents that electric vehicles can cause at low speeds due to their quiet engine operations, the function and adequacy of AVAS remain a technical challenge - especially in urban areas where background noise may create a masking effect (see e.g., Altinsoy, 2013; Cai and Moreno, 2024; Hsieh et al., 2021; Parizet et al., 2014; Poveda-Martínez et al., 2017; Yamauchi et al., 2014). In a safety manner, this problem manifests itself even worse in heavy electric vehicles since their braking distances are longer, their momentum is greater and they have more blind spots (FMCSA, 2021). Therefore, further investigation is necessary for a better understanding of the safety function of AVAS in noisy urban environments, as well as to point out current and future requirements of AVAS.

In this regard, the main motivation of this study is to contribute to the safety aspects of BEV heavy trucks[1] by examining the functionality of their sound from AVAS in urban areas, thus helping to create a safer traffic environment for vulnerable road users. Two main questions are addressed: whether electric truck sounds are distinguishable from electric cars and whether they are accurately detectable at safe distances in urban environments, considering the potential for urban background noises to mask AVAS sound. Detailed research questions can be found in Section 1.3. To answer these main questions, listening tests were conducted, which are comprehensively explained in Chapter 3.

The following sections provide the foundation of the present study, explain why these research questions are worth addressing, and discuss the study's limitations. The chapter concludes with the thesis structure, which outlines the overall organization of the thesis.

[1] In the present study, heavy trucks in Category N3, which are used for the carriage of goods and have a mass exceeding 12 tonnes, are utilized. This classification applies to the trucks involved in this research, even though it is not explicitly mentioned in the subsequent sections.

1.2 Background of the Thesis

1.2.1 Exploring AVAS: Necessity, Global Efforts, and Regulations

Acoustic Vehicle Alerting System (AVAS) uses loudspeakers to emit artificial sound when vehicle is moving at low speeds (currently up to 20 km/h (UNECE, 2017) and 30 km/h (NHTSA, 2020) for European and American Regulations, respectively).

Debates on the necessity for additional warning systems come back to the late 2000s when hybrid and electric vehicles gained popularity. The National Federation of the Blind (NFB) has raised awareness in the United States about the risks electric and hybrid vehicles pose to pedestrians (NFB, 2007) and has helped establish regulations enabling pedestrians to detect approaching vehicles. Following NFB, persistent campaigns by the World Blind Union (WBU, 2013), the Japan Federation of the Blind (MLIT, 2010), the European Blind Union (EBU, 2017), and the Royal National Institute of Blind People in the United Kingdom (RNIB, 2019) has been played a vital role in the worldwide adoption of AVAS.

In addition to advocacy efforts, initial studies conducted between 2009 and 2010 were crucial in revealing the dangers that silent vehicles could cause. To illustrate the National Highway Traffic Safety Administration (NHTSA) compared the incident rates of Hybrid Electric Vehicles (HEVs) and Internal Combustion Engine vehicles (ICE), their finding showed that the percentage of hybrid vehicles involved in accidents was twice as high as ICE vehicles (Hanna, 2009). NHTSA's further study focused on safety of blind pedestrians, The study highlighted that HEVs' quieter operation at low speeds was making it harder for blind pedestrians to detect them, as well as increasing the likelihood of a crash. They suggested adding artificial sounds and implementing regulatory procedures to ensure pedestrian safety (Garay-Vega et al., 2010). Another study aligned with this study was conducted by the Society of Automotive Engineers (SAE). The research revealed that blind test participants could recognize vehicles from the engine sound they heard at low speeds and that this noise was the most effective auditory warning. Vehicles were detected by subjects when their sound levels were 2 dB above the background levels. Their finding revealed that additional alerting systems were required to improve safety but can be implemented without creating noise pollution(Goodes et al., 2009).

In light of research findings and campaigns, Japan became the first country to mandate AVAS for hybrid and electric vehicles in 2010 (MLIT, 2010). This was the beginning of a global trend. From 2011 to 2018, countries began to prepare their own AVAS regulations. As of July 1, 2019, the EU required all new types of electric and hybrid vehicles to have AVAS, and as of July 1, 2021, this requirement has been extended to include older models (UNECE, 2017). The US fully implemented AVAS regulations in 2020 (NHTSA, 2020), and China followed suit in 2021. In 2023, Australia adopted EU regulations (DITRDCA, 2023).

The EU Regulation mandates that AVAS in electric and hybrid vehicles must produce sounds within specific frequency ranges, ensuring minimum sound levels in two one-third octave bands within the range of 160-5000 Hz, and with at least one band above 1600 Hz. Additionally, the sound frequency should adjust by at least 0.8 % per 1 km/h within the speed range of 5-20 km/h when the vehicle is moving forward. The vehicle must also emit a minimum sound level of 50 dB(A) at 10 km/h and 56 dB(A) at 20 km/h, measured on an ISO 10844 road surface (ISO, 2021), 2 meters from the track center, and a height of 1.2 meters. The sound should not exceed the noise level of a conventional vehicle and must remain below 75 dB(A) (UNECE, 2017).

1.2.2 AVAS in Trucks: Key Differences in Safety Aspects

Vulnerable road users (VRUs) account for the highest proportion of road fatalities in urban areas: pedestrians, motorcyclists, and cyclists account for 23, 21, and 6 %, respectively, and 53 % overall (WHO, 2023).

The risk of serious injury and death caused by accidents involving trucks is higher than cars (Desapriya et al., 2010) mainly due to cars and trucks differing significantly in size, weight, momentum, braking distances, and blind spots (FMCSA, 2021). For instance, although trucks on the roads in the European Union are only 2 % (EC, 2024a), they are responsible for approximately 15 % of fatal crashes (EC, 2020).

As of 2023, electric trucks represent 0.1 % of all trucks on the EU roads (ACEA, 2023). By 2030, it is projected that electric trucks will make up approximately 9.2 % of the total truck fleet in Europe (Statista, 2024). Currently, AVAS regulations in the EU do not differentiate between cars and trucks. On the other hand, the differentiation between AVAS in cars and trucks - by varying the sound patterns and frequencies- is essential for improving situational awareness and preventing accidents, especially for visually impaired road users who rely on acoustic clues. For example, a recent study highlights the need to differentiate AVAS sounds, so electric trucks can effectively convey their presence (Kullukcu et al., 2024).

Moreover, urban policy planners aim to reduce car dependency, improve public transport, and impose speed limits in city centers. Although the ultimate goal is to decrease personal vehicle use, the need to deliver goods to city centers will continue, making the role of delivery trucks even more critical, especially in urban areas. In addition, as efforts are made to tighten emission regulations and transform cities into low-emission zones, electric trucks stand out for their ability to easily comply with these new standards, enabling logistics support to continue their operations without interruption. European Commission's Sustainable Urban Mobility Plans (SUMPs) emphasize integrating electric trucks to create more sustainable city environments (EC, 2024b). For instance, Stockholm plans to reduce car traffic by 30 % by 2030 while increasing the use of electric trucks (EC, 2023), and London's Freight and Servicing Action Plan aims to limit freight vehicles during peak hours and promote electric alternatives (TfL, 2019).

With the increased presence of electric trucks in vehicle fleets in the future, designing proper AVAS sounds will be more critical for preventing truck-involved accidents and enhancing safety in urban environments.

1.2.3 Relevance of AVAS Research to Sustainable Development Goals

Research on Acoustic Vehicle Alert Systems (AVAS) is closely linked to several United Nations Sustainable Development Goals (SDGs)[2] that address safety and sustainability in urban environments. Here is a summary of how AVAS research contributes to these global goals:

SDG 3: Good Health and Well-being
Research on AVAS could improve pedestrian safety, especially for the visually impaired, by making electric vehicles more detectable. By doing this, it helps improve public health and well-being. Moreover, well-designed AVAS sounds preserve the advantages of the quiet nature of EVs without compromising safety and prevent urban quiet areas from being negatively impacted, ultimately helping to reduce stress in urban areas.

SDG 10: Reduced Inequality
At its core, AVAS research addresses the needs of visually impaired individuals, so it helps to tackle a particular inequality in urban mobility. Ensuring that the functionality of AVAS is adequate and effective helps create safer urban environments for society as a whole.

SDG 11: Sustainable Cities and Communities
Research on AVAS is intrinsically linked to sustainable urban development as it paves the way for the safe integration of EVs into urban areas and enables the design and planning of safer, more inclusive living environments. These studies could also give insights into urban sound planning if trade-offs between safety and preservation of quiet urban areas are considered while designing AVAS sounds (Laib & Schmidt, 2019; SINTEF, 2019).

SDG 13: Climate Action
Research on AVAS indirectly contributes to the ongoing energy transition by supporting EV adoption safely and inclusively in urban areas. Thereby helping to mitigate climate change by removing one of the barriers to increased EV use in

[2] After decades of international efforts, including the 1972 Stockholm Conference (UN, 1972), the 1987 Brundtland Report (WCED, 1987), the 1992 Earth Summit (UN, 1993) and the 2012 Rio+20 Conference (UN, 2012), Sustainable Development Goals were established by the United Nations in 2015, replacing the Millennium Development Goals (UN, 2000). The SDGs focus on addressing global challenges such as poverty, inequality, and climate change by 2030, working towards being universal, integrated, and inclusive (For more information about the SDGs, please refer to UN, 2015).

cities.

1.3 Aim of the Research

Research on AVAS aligns with several sustainable development goals as mentioned in the previous section (see Section 1.2.3). While the research context is comprehensive, this study specifically hones in on the crucial safety aspect of AVAS for trucks. By prioritising on safety perspective, this research aims to contribute better understanding of AVAS effectness in urban areas, to ensure insights into current and future needs of designing AVAS sounds for electrified trucks. More specifically, the goal of the research is to seek answers to the following questions & sub-questions by performing listening tests. Figure 1.1 shows the schematic version of these questions.

Q1. How accurately can pedestrians **classify** sounds as coming from cars or trucks under different conditions?

A. Can pedestrians accurately classify vehicles when there is no time constraint?
B. Can pedestrians accurately classify vehicles within stimuli duration?
C. Can pedestrians accurately classify vehicle sounds at safe distances?

Q2. How accurately can pedestrians **detect** and classify vehicles amidst continuous urban background noise?

A. Can pedestrians detect vehicles amidst continuous urban background noise?
B. Can pedestrians accurately classify the detected vehicles?
C. Can pedestrians detect vehicles at safe distances?
D. Can pedestrians accurately classify the vehicles that are detected at a safe distance?

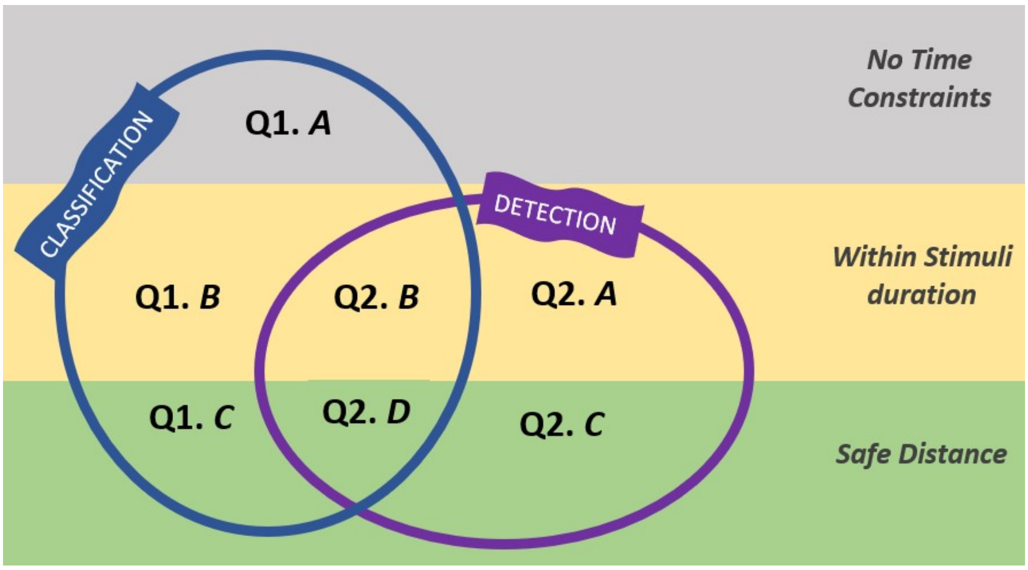


Figure 1.1: Schematic Representation of the Research Questions.

1.4 Limitations of the Research

This study has some limitations that should be acknowledged when interpreting the results.

1.4.1. Limitations Due to Test Materials

Brand-Specific AVAS Sound: Only one brand's AVAS sound and its versions were used in the study. Although the regulation imposes restrictions on how AVAS sounds should be, it leaves room for brands to produce and use their signature sounds. Therefore, the AVAS sound used may not represent the sounds of other brands, which may affect the generalization of this research findings.

Vehicle Variety: Contrary to the ideal situation, the number of vehicles used in the study was limited. More generic results may be obtained by testing the sounds from more vehicles - also from different brands.

The vehicles used in the research consist of one electric car (EV), one internal combustion engine (ICE) car, one battery electric vehicle (BEV) truck with five different AVAS versions, and one ICE truck. Unlike this study, considering the current proportion of the vehicle fleet in urban areas, there are more cars and fewer trucks. For this reason, the study does not fully reflect real urban areas in this manner.

Urban Soundscapes: Although the background sounds used in the study were recorded from various parts of the city, they were recorded in a single city, Stockholm. Sound levels, diversity of noise sources, and their frequency contents may vary from city to city, and this may affect the detection and classification of vehicle sounds and, thus study findings.

1.4.2. Limitations Due to Operation

Vehicle Speeds: Tests were conducted at two different speeds, constant speeds of 10 and 20 km/h, respectively. This resulted in not considering dynamic speed changes (acceleration or deceleration) typically encountered in real-world driving conditions.

Binaural Head Position: Only one binaural head position was used during listening tests. Since changes in head position may affect the perception of sound, it may affect the findings of the resulting study.

Weather Conditions: Factors that would affect braking distances, such as different weather conditions - rainy or icy ground - were eliminated in the study, only "dry" weather condition is considered. As a result, this potentially limited the study's applicability to various environmental conditions.

1.4.3. Limitations Due to the Method

Listening Tests: The study was conducted through listening tests and the sounds were reproduced with headphones that have active noise control. Therefore, any limit caused by using a listening test as a method is also applied to this study. The limits caused by the use of headphones are also the limits of this study. Additionally, the study was completed using 4 different rooms, in other words, not every participant participated in the test in the same room. Although high-quality headphones with active noise control were used, this can be considered a study limitation.

Signal Detection Theory: Conducted listening tests were grounded in signal detection theory, so all limitations of signal detection theory also apply to this study.

1.5 Structure of the Thesis

The introduction begins by explaining the necessity of this research. The background section provides relevant information leading to the study. Then, it states the aims and objectives of the study, followed by a summary of the study's limitations.

The second chapter presents the literature review with a thematic approach. The literature review systematically examines the relevant studies, their findings, and methodologies. It identifies research gaps, thus strengthening the need for research and laying the groundwork for current studies.

The third chapter details the methodology, which consists of three main parts. The first part describes each step while preparing for listening tests, including recording background sounds and measuring vehicle sounds from cars and trucks. The second section provides comprehensive information about the listening test procedure and its interface. The last section outlines the instructions for the listening tests, detailing the step-by-step process followed during the tests.

The fourth chapter presents the analysis of the results and discusses the research findings in the context of the aims and objectives of the research. After presenting the study outcomes, the chapter ends with a discussion of the role of AVAS in future urban areas.

The last chapter highlights the main findings and their significance. It also offers suggestions for future research that may contribute to the field.

2

Literature Review

The main goal of this chapter is to look into previous research with a thematic approach rather than a chronological one. Reviewed articles were mainly collected using snowballing technique, with selecting a reference point as one of the past EU Projects, eVADER[1], namely. The project focused on safe operation of EVs in general and some cohorts of the project specifically investigated to improve the acoustic detectability of EVs in urban areas.

The literature review has been started through the articles and conference papers, which are the mentioned project's outcomes[2]. Then searching those articles's references collected a fair amount of research, and benefiting from their keywords, more current research in the field has been reached out. Collected documents were scanned through to determine the relevancy of the study, the ones were eliminated whether their aim was out of the scope of this study. 56 studies were selected for further exploration, which included 27 journal articles, 22 conference papers or proceedings, 3 PhD or MSc thesis, 1 book chapter and 3 technical reports.

Consequently, the selected studies were categorized into two groups: empirical studies (43 of 56 studies) and policy, regulation, and planning-related studies (13 of 56 studies). The second group, i.e. policy, regulation, and planning-related studies, was separated to discuss the future function of AVAS in Section 4.4.

The first group, empirical studies, was further divided into 6 groups, considering the main research focus. These groups can be listed as follows:

1. Detectability of AVAS (20 of 43 studies).
2. Detectability of AVAS and annoyance due to AVAS (7 of 43 studies).
3. Annoyance due to AVAS (3 of 43 studies).
4. Design of AVAS sound (5 of 43 studies).
5. Community acceptability of AVAS (5 of 43 studies).
6. Effect of AVAS on urban soundscapes (3 of 43 studies).

[1]The project was conducted between 2011 and 2014, with a collaboration of 11 partners in 7 countries, more information about the project can be found in https://cordis.europa.eu/project/id/285095.

[2]The publication list can be accessible via https://cordis.europa.eu/project/id/285095/results.

Figure 2.1 shows how these categories are distributed in the collected research. As seen, the main contribution from previous research comes through detectability of AVAS (46%), the following research focus is both detectability and annoyance (16%). Previous research rarely focused solely on annoyance (7%) or how AVAS affect urban soundscapes (7%).

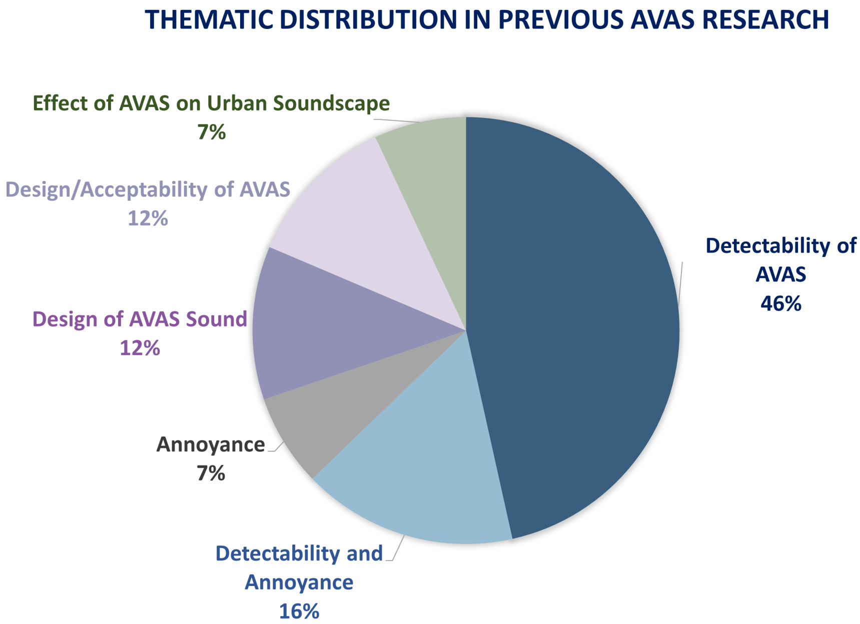


Figure 2.1: Thematic Distribution in Previous AVAS Research.

Table 2.1 summarizes the methodologies used in previous research. Studies that focused on detectability, annoyance, or both mainly preferred to conduct either listening tests (Altinsoy, 2013; Cai and Moreno, 2024; Garay-Vega et al., 2011; Ishiyama and Hashimoto, 2000; Kerber and Fastl, 2008; Kullukcu et al., 2024; Misdariis et al., 2013; Parizet et al., 2014; Parizet et al., 2016; Poveda-Martínez et al., 2017; Yamauchi et al., 2015) or in-situ tests (Berge and Haukland, 2019; Chamard and Roussarie, 2012; Emerson et al., 2011; Fleury et al., 2016; Glaeser et al., 2019; Hsieh et al., 2021; Kim et al., 2012; Lucas et al., 2017; Roan et al., 2021. The visual sense is rarely combined with the hearing sense (Oberfeld et al., 2022; Soares et al., 2020) while focusing detectability and/or annoyance. Even in in-situ tests, blindfolding (e.g. Fleury et al., 2016) or sleep shades (e.g. Berge and Haukland, 2019) eliminated visual cues for sighted participants.

The main goal for detection-focused studies was to explore the detection times of the participants and distances corresponding to detection times accordingly to check whether vehicles can be detected at safe distances enough to prevent possible accidents. As a result, participants were tasked to react once they heard approaching vehicles. Among previous research, two exemptions stand out. In their field tests, Emerson et al., 2011 focused on their participants' willingness to cross the road.

Table 2.1: Methodologies Used in Previous Research on AVAS.

Study Focus	**Methodology**				
	Listening Test	**In-situ Test**	**Audio-Visual Test**	**Questionnaire/ Interview**	**Measurements/ Simulations/ Experiments**
Detectability of AVAS	Altinsoy, 2013 Cai and Moreno, 2024 Garay-Vega et al., 2011 Kerber and Fastl, 2008 Misdariis et al., 2013 Parizet et al., 2016 Yamauchi et al., 2015 Parizet et al., 2014 Poveda-Martínez et al., 2017	Berge and Haukland, 2019 Chamard and Roussarie, 2012 Fleury et al., 2016 Glaeser et al., 2019 Hsieh et al., 2021 Kim et al., 2012 Lucas et al., 2017 Roan et al., 2021 Emerson et al., 2011	Oberfeld et al., 2022 Soares et al., 2020		
Detectability and Annoyance	Bazilinskyy et al., 2023 Jacobsen et al., 2020 Lee et al., 2017 Steinbach and Altinsoy, 2020 Steinbach and Altinsoy, 2019 Steinbach et al., 2017 Yamauchi et al., 2014				
Annoyance	Ishiyama and Hashimoto, 2000 Kullukcu et al., 2024 Parizet et al., 2016				
Design of AVAS Sound	Sigman and Misdariis, 2014		Misdariis et al., 2012		Kournoutos, 2020 Quinn et al., 2014 Souaille et al., 2022
Design/ Acceptability of AVAS	Fagerlönn et al., 2018 Wogalter et al., 2014	Fagerlönn et al., 2018	Shirnazar, 2020 Nyeste, 2008	Fontecha et al., 2022 Shirnazar, 2020 Wogalter et al., 2014	
Effect of AVAS on Urban Soundscape					Genuit, 2013 Laib and Schmidt, 2019 Pallas et al., 2023

In other words, they wanted to explore while crossing the road which distances pedestrians feel safe enough to cross the road while approaching EV vehicles. In their online listening tests, Bazilinskyy et al., 2023 investigated when pedestrians felt safe to cross the road. They tasked them to hold pressing the button until the participants felt threatened or in danger anymore.

During the in-situ tests, subjects were placed edge of the road or very close to the specified road facing the road and waiting to cross over the road. Likewise in listening tests, the stimulus was measured for crossing the road scenario, supposing that pedestrians were waiting to cross over the road. An exception was the study conducted by Cai and Moreno, 2024. In their research, pass-by vehicle sounds were measured behind the binaural head and then investigated via listening tests, supposing vehicles were approaching behind the pedestrians.

Listening tests were conducted mainly via headphones (45%), while 27% of them were conducted via loudspeakers (Figure 2.2).

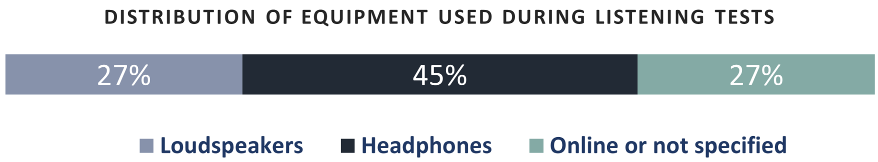


Figure 2.2: Distribution of Equipment Used in Listening Tests in Previous AVAS Research.

Previous research investigated the possible masking effect of urban background noises on AVAS. While investigating the masking effect, they preferred either recorded sounds from urban soundscapes playback with vehicle sounds together during the listening tests (see e.g. Altinsoy, 2013; Parizet et al., 2014; Poveda-Martínez et al., 2017) or playback of recorded urban background noises via loudspeakers behind the participants in the field tests (see e.g. Berge and Haukland, 2019; Chamard and Roussarie, 2012; Lucas et al., 2017).

Some studies used one additional background noise (see e.g. Kerber and Fastl, 2008; Steinbach and Altinsoy, 2019), while some researchers wanted to investigate the effect of sound levels (see e.g. Misdariis et al., 2013; Yamauchi et al., 2015)or frequency content of the background noises(see e.g. Parizet et al., 2014; Poveda-Martínez et al., 2017). Therefore they preferred more than one sound with varying levels (see e.g. Cai and Moreno, 2024; Hsieh et al., 2021; Roan et al., 2021). Some researchers preferred to use white noise instead of recorded soundscapes (see e.g. Jacobsen et al., 2020; Lee et al., 2017) or did not prefer to use additional background noises especially if they conducted in-situ tests(see e.g. Emerson et al., 2011; Glaeser et al., 2019).

Figure 2.3 shows the analysis of the background sound levels used in the previous research. 41 levels were specified and used in the studies, with a mean of 57.8 dB(A), with 31.2 as the lowest level and 73.2 as the highest level used in research.

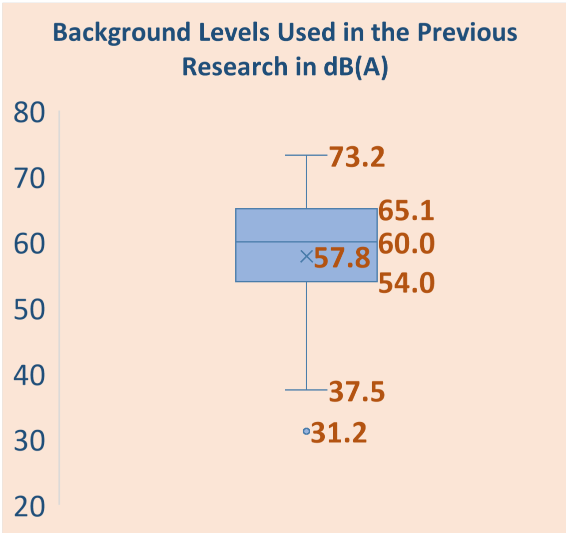


Figure 2.3: Urban Background Levels Used in Previous AVAS Research.

Researchers rarely tested electrified heavy vehicles, majority of the vehicles tested in previous research belong to light vehicles (Figure 2.4). Only 3 of the collected research focused on heavy vehicles (as the author's best knowledge there is no more research on focusing safety aspect of electrified heavy trucks regarding AVAS).

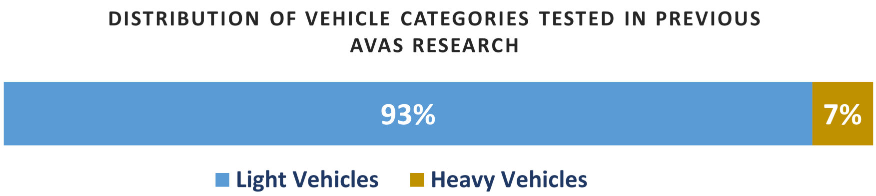


Figure 2.4: Distribution of Vehicle Category Tested in Previous AVAS Research.

In their master's thesis, Shirnazar, 2020 studied the effect of additional take-off sounds on AVAS for trucks. Their findings suggested that adding these sounds improves the safety function of AVAS. Kullukcu et al., 2024 explored the possible suitable AVAS sounds for electric trucks and focused psychoacoustic aspects of the warning sounds. Their suggestion was for ensuring ”truck-likeness” perception (without adding annoyance), trade-offs between spectral content, tonality peaks, and roughness are vital to consider.

In their research project, Fontecha et al., 2022 focused on Transport for London's (TfL) electrified bus fleets. Through comprehensive measurement campaigns, data monitoring, interviews with bus drivers and on-street surveys, they investigated community acceptance of electrified public transportation as well as possible contributions to the environment or effects on society. They also consider adaptive (responsive) AVAS solutions. Their finding revealed that electric buses outperformed their combustion counterparts in environmental aspects, and adaptive AVAS solutions promise more positive results than normal AVAS regarding environmental aspects. On the other hand, street surveys and interviews suggest that both drivers and citizens are not fully convinced about the safety aspects of electric buses, especially under busy noisy urban circumstances.

3 Methodology

This chapter explains the study's methodology in detail and consists of three main parts. The first part describes each step while preparing for listening tests, including recording background sounds and measuring vehicle sounds from trucks[1] and cars. The second section provides comprehensive information about the listening test procedure and its interface. The last section outlines the instructions for the listening tests, detailing the step-by-step process followed during the tests.

To address the research questions presented in Section 1.3, listening tests were conducted with 51 participants between June 11 and June 28, 2024. The vast majority of these participants work at KTH or Scania CV AB. Descriptive statistics of the participants are analyzed in Section 4.1. With the advantage of a portable setup and using headphones, the listening tests were conducted in four different rooms: two at Scania and two at KTH. This flexibility allowed for a more customizable schedule for testing and enabled the inclusion of more participants than initially foreseen. On the other hand, this situation evolved into one of the limitations of this study, as not all participants experienced the same environmental settings, despite using high-quality headphones with active noise control.

3.1 Preparation of the Listening Test

The theory behind listening tests is fundamentally grounded in the masking effect and signal detection theory, briefly summarized in the following section, just before starting to explain how the tests were prepared.

3.1.1 Theoretical & Conceptual Foundations of the Test

Both the masking effect phenomenon and signal detection theory are highly relevant to psychophysics[2], which digs into finding quantitative relationships between physical stimuli and resulting perceptions produced by the stimuli. For example, in

[1] In the present study, heavy trucks in Category N3, which are used for the carriage of goods and have a mass exceeding 12 tonnes, are utilized. This classification applies to the trucks involved in this research, even though it is not explicitly mentioned in the subsequent sections.

[2] Psychophysics began to be studied in the early 19th century, for information about the history of psychophysics refers to Murray's article (Murray, 1993), which scrutinized the development of psychophysics from Gustav Theodor Fechner to the 1990s. For a more comprehensive theoretical and methodological knowledge in the field, which covers classical and modern applications, refer to Gescheider's book (Gescheider, 1997).

the field of acoustics, sound waves are the physical stimuli, and here, psychophysics focuses on how these sound waves are perceived by the human auditory system quantitatively.

3.1.1.1 Masking Effect

Masking effect is widely studied in auditory literature[3], as one of the rooted concepts of hearing. It can simply be defined as a situation where one sound(s) makes it harder to hear another sound. Due to it being nearly impossible to hear only one sound at a time, masking is a common phenomenon in everyday life. However, its compelling effect is encountered when it becomes difficult to hear or follow the targeted sound due to the presence of other sounds (Oxenham, 2013).

Definition and the depth of understanding of the masking effect have expanded over the years and have been addressed from different perspectives, with "energetic masking" and "informational masking" standing out as two widely adopted and used categorizations in the field (Hao et al., 2016). Informational masking is typically viewed as a complementary concept to energetic masking and is often linked and compared with it (Kidd et al., 2008). To illustrate, consider being in a noisy environment. Noise can interfere with a speech signal in two primary ways. If the noise interferes with the speech signal in the physical environment, it is known as energetic masking. On the other hand, if the noise interferes with the target signal during the perceptual process, it is referred to as informational masking (Lidestam et al., 2014). An example of energetic masking is attempting to hear someone over loud music and an example of informational masking is trying to concentrate on one conversation in a room where many people are talking.

3.1.1.2 Signal Detection Theory (SDT)

As mentioned at the beginning of the chapter, SDT is closely tied and be applied to psychophysics. The main goal of the SDT is to provide a quantitative framework[4] by considering the sensitivity of the subjects and their decision-making-process as a result of physical stimuli, thus measuring the capability to differentiate between the desired signal and non-target signals, i.e noise. Although SDT can be described in many ways, the one below (Gelman & Cortina, 2012) summarizes the theory's nature in short but comprehensively:

> *"SDT is a theory of behaviour in imperfect performance domains such as perception, where there is human error and much of our performance is in some sense probabilistic."*

[3] The earliest work on masking is generally thought to have begun with a series of experiments conducted by Bell Labs researchers, particularly during the early to mid-20th century (Kidd et al., 2008), and more detailed information about historical perspectives on masking phenomenon can be found in the same reference (Kidd et al., 2008).

[4] For calculation and modelling basics refer to Gescheider's book (Gescheider, 1997), Chapters 5 and 6.

In this regard, besides physical impairments subjects' impression and perception can be affected not only by the physical environment but also by subjects' motivation, particularly if subjects are asked to complete a complex task (Gelman & Cortina, 2012). In other words, what SDT provides is not a focus on "correctness" or "perfection", but rather a framework for quantifying subjects' outputs, which naturally include imperfections and errors.

3.1.1.3 The Relevance of Masking Effect and SDT in this Listening Test

The conducted listening test consists of two main parts "Classification" and "Detection & Classification", namely, these parts will be explained with the procedure and the tests interface, in more detail in the following sections. At this point, it is pertinent to discuss how masking effect and SDT are related to the listening tests' parts.

In the first part of the listening test, participants classified sounds (truck or car) with a low background noise level of around 45 dB(A), therefore this task primarily involves informational masking, as the background noise is not high enough to significantly interfere with the target sounds. Here, the main challenge for participants is distinguishing between the sounds, such as a truck and a car, without much interference from the background noise. At this juncture, SDT provides a theoretical basis for measuring how informational masking affects the classification process by examining the participants' accuracy in identifying the target sounds (hits) versus incorrectly identifying them (misses).

In the second part, participants detected vehicle sounds against a continuous, additional urban background noise of around 60 dB(A) and then classified them as either trucks or cars. During the detection task, energetic masking plays an important role due to the higher background noise level, which can physically interfere with the vehicle sounds, making them harder to detect. In addition to this, since the background noises also include traffic noise, this task secondarily involves informational masking. Once the vehicle sounds are detected, the classification task again involves informational masking, as participants need to distinguish between similar sounds amidst the background noise. In summary, the second part of the test involves both energetic and informational masking. In this context, the role of SDT is to quantify the detection rates by examining the proportion of detected sounds (hits) and missed sounds (misses). Signal-to-noise ratios (SNR) also have been calculated in order to quantify the relationship between the signal and the background noise. Similarly to the first part of the test, SDT helps to analyze correct and incorrect classifications again, since participants also classify the sounds after detections. However, in this part, the classification task is conducted amidst higher background noise, with the dominance of energetic masking.

In conclusion, the design of the listening test, which included both "Classification" and "Detection & Classification" tasks, was naturally based on the concept of masking effect and grounded with the principles of SDT.

3.1.2 Preparation of Audio Files for the Test

To address the research questions, the listening test is divided into two main parts, "Classification" and "Detection& Classification". As their name suggests, during the first part, subjects were asked to classify vehicle sounds as either a truck or a car, while in the second part, they were tasked with detecting vehicle sounds within additional urban background noise and then classifying the detected one.

The main differences between the parts were due to the complexity of the tasks and the background noise levels. In the classification part of the test, vehicle sounds were presented without additional background noise. However, since these sounds were measured in outdoor environments, the files inevitably included some background noise. In the second part of the test, there were 15 one-minute audio clips, each within continuous urban background noise. Vehicle sounds were presented within these continuous background noises for detection and then classification.

Before detailing the procedure of the test and its interface, Section 3.1.2.1 and Section 3.1.2.2 explain how truck and car sound measurements were performed and how urban background noises were recorded, respectively.

3.1.2.1 Measurement of Vehicle Sounds

Measurements were conducted using four different vehicles: a BEV Heavy Truck, an ICE Truck, a BEV Passenger Car, and an ICE Passenger Car. The electric truck was tested under three conditions: with the Acoustic Vehicle Alerting System (AVAS) active, without AVAS, and with modulated[5] AVAS sound. Additionally, the tonal components originating from the Hydraulic Steering System (EHS) were reduced by 12 dB by applying a filter in the BEV truck's measurement files, both with AVAS and without AVAS. The filtered versions of the files were included in listening tests to understand whether the audibility of AVAS is influenced by the tonal components, also considering that future generations of the truck may not have these dominant tonal components

In total, six distinct vehicle sounds were measured (ICE Truck, BEV Truck-AVAS on, off, modulated AVAS-, BEV Car, and ICE Car). Then two more BEV Truck sounds were obtained through filtering its tonal components, consequently **eight distinct vehicle sounds** were used in the tests. Since each vehicle measured at **two different speeds**, 10 km/h and 20 km/h, this resulted in a total of **16 different sound files**.

Vehicle sound measurements were conducted in four different campaigns. Truck measurements were performed on the 23rd and 28th of March 2024 at the Scania Test Track in Södertälje, Stockholm. BEV car measurements were carried out on the 12th of April 2024 at the KTH campus (Drottning Kristinas väg), and ICE car

[5]Amplitude modulation is applied using a 20 Hz carrier sine signal, where modulation factor is 0.4

measurements were conducted on the 25th of May 2024 in Uppsala.

Table 3.1 summarizes all the vehicle sounds presented in the test and includes their abbreviations, which are used when presenting the results both in graphs and text in Chapter 4.

Table 3.1: Vehicle Sounds Used in the Test and Their Abbreviations.

Condition	Description
BEV Heavy Truck (Category N3)	
AVAS ON 10	BEV Truck With AVAS, 10 km/h
AVAS ON 20	BEV Truck With AVAS, 20 km/h
AVAS OFF 10	BEV Truck Without AVAS, 10 km/h
AVAS OFF 20	BEV Truck Without AVAS, 20 km/h
MOD AVAS 10	BEV Truck Modulated AVAS, 10 km/h
MOD AVAS 20	BEV Truck Modulated AVAS, 20 km/h
F AVAS ON 10	BEV Truck's tonal components filtered, With AVAS, 10 km/h
F AVAS ON 20	BEV Truck's tonal components filtered, With AVAS, 20 km/h
F AVAS OFF 10	BEV Truck's tonal components filtered, Without AVAS, 10 km/h
F AVAS OFF 20	BEV Truck's tonal components filtered, Without AVAS, 20 km/h
ICE Heavy Truck (Category N3)	
ICE TRUCK 10	Diesel Truck, 10 km/h
ICE TRUCK 20	Diesel Truck, 20 km/h
Passenger Cars	
EV CAR 10	BEV Car, 10 km/h
EV CAR 20	BEV Car, 20 km/h
ICE CAR 10	Gasoline Car, 10 km/h
ICE CAR 20	Gasoline Car, 20 km/h

Figure shows the schematic representation of the measurement setup.

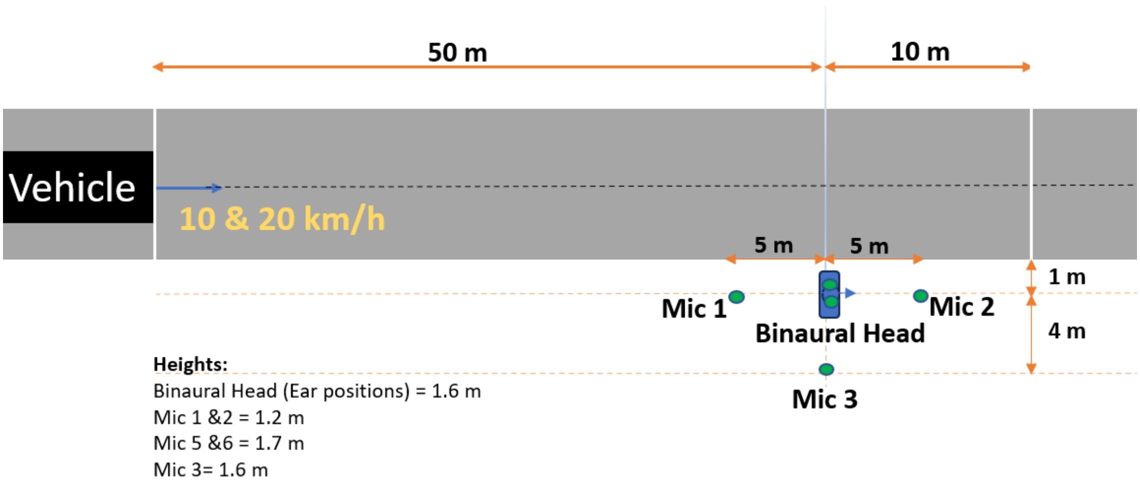


Figure 3.1: Schematic Representation of the Measurement Setup.

Measurements were taken 50 m away from the binaural head and continued for 10 meters after passing it. The ear positions were 1.6 m above the ground. Two positions of the binaural head were carried out:

1. The binaural head facing to the road (supposing that a pedestrian waiting to cross the road).
2. The binaural head facing along the road (supposing that vehicles approaching from behind of the pedestrian)

Although measurements were performed in both positions, the latter was selected for the test (vehicles approaching from behind) due to representing a more challenging scenario for sound capture due to the ear positions and lack of visual cues for the pedestrian.

In the selected scenario, vehicles approaching from behind of the pedestrian, the binaural head was positioned 1 meter from the edge of the road, with the left ear 90 cm, and the right ear 110 cm from the road edge. 5 free field microphones were used for verification purposes of whether the microphone measurements were in correlation with binaural head measurements. As seen in Figure 3.1, two of them were 5 m away from the binaural head and were set at a height of 1.2 m. The farther positioned microphone to the road edge was 5 m away, and 4 m away from the binaural head, and was set at a height of 1.6 m. The remaining two microphones were positioned very closely to the binaural head, approximately 15 cm away positioned horizontally from the binaural head's ears, and were set at a height of 1.7 m.

Equipment for truck measurements includes a binaural head (HEAD acoustics HMS III electric), light barriers (for triggering the system and starting the measurements exactly from 50 m away), 5 free field microphones (G.R.A.S), windshields (for both the microphones and the binaural head).

Measurements were conducted in dry asphalt conditions, with **low wind** and **no precipitation**. **Background noise** measurements were performed intermittently on the site, they were around **45 db(A)**. Figure 3.2 presents a collage of photos taken during the sound measurements of the BEV truck.

Post-processing of the measurements began with exporting the **sound files** from ArtemiS SUITE (v.14) Software[6] in WAV format, 24 bits, 48 kHz. Then imported into Audacity[7] Software(v.3.4.2). The files captured the vehicle pass over a total distance of 60 m (Measurements started 50 m before the binaural head and continued for 10 m after passing it). The files were trimmed to include only this 60-meter segment. Fade-in and fade-out were applied to each file as 1 second. In addition, a high-pass filter was used to remove wind noise, eliminating frequencies below 30

[6]More information about the analysis software can be found in https://www.head-acoustics.com/products/analysis-software/artemis-suite.

[7]Audacity is an open source software for recording and editing audio, detailed information can be accessed via https://www.audacityteam.org/FAQ/.

Hz. Furthermore, the BEV Truck's tonal components were reduced by 12 dB using a filter in Audacity Software, both with and without AVAS. Thus two more BEV Truck files were added to the test, and consequently, 12 distinct truck sound files were obtained (see Table 3.1). The files were then re-exported in WAV format, 24 bits, 48 kHz. It is worth mentioning that due to the different vehicle speeds (10 km/h and 20 km/h) over the same distance (60 m in total), the resulting stimulus durations were 22 seconds and 11 seconds, respectively.

Figure 3.2: Photos Taken During BEV Truck Measurements, Scania Test Track, Södertälje.

For **Passenger car measurements**, the equipment was different from truck measurements. The equipment includes a binaural head with windshields, an external sound card (Focusrite Scarlett 2i2), and Audacity Software for measurements. Unlike the truck sound measurements, free-field microphones for verification purposes were not used for car measurements. Like truck measurements, passenger car measurements were also carried out 50 m away from the binaural head and continued for 10 m after passing it, with one exceptional case, the ICE Car[8] (10 km/h).

Other settings were identical: The ear positions were 1.6 m, and the measurement was performed while the binaural head was facing away from the road (simulating vehicles approaching from behind). The same distance was used as with truck measurements, i.e., from the edge of the road, the left ear was 90 cm and the right ear

[8]The ICE Car was measured from approximately 30 meters away from the binaural head and continued for 10 meters after passing it, 40 m distance in total, resulting in a 13-second file duration, different from the other 10 km/h vehicle sound files, which were 22 seconds. During the listening tests, this 13-second file was used. However, for analysis, 9 seconds were added to the participants' classification time responses to compensate for the 20 m difference. By doing this, a fair comparison of classification and detection times across all vehicle sounds was ensured .

was 110 cm.

Measurements were conducted in dry asphalt conditions, with **low wind** and **no precipitation** and a **background noise level** around **45 dB(A)**. However, important to note that since they were performed in springtime, background noises included more bird noises in comparison to the truck sound files (On the other hand, truck sound files also included bird noises but not as dominantly as the car sound files, since truck sounds were measured at the end of March). To reduce these clues from the audio files, as will be mentioned in the following section, urban background noises were mixed with bird sounds.

Post-processing of the passenger car measurements was conducted similarly to the truck measurements. **Sound files** were prepared by applying an almost identical procedure to that used for the truck sound files, except at the beginning, where Audacity software was used for the measurements instead of ArtemiS Suite software. The remaining part of the procedure was identical. The files were trimmed to include 60 m segment (except ICE car 10 km/h, please see the Footnote 8). Fade-in and fade-out were applied to each file as 1 second. And again, a high-pass filter was used to remove wind noise, eliminating frequencies below 30 Hz. 4 distinct car sound files were obtained (see Table 3.1). The files were exported in WAV format, 24 bits, 48 kHz. Due to the different vehicle speeds (10 km/h and 20 km/h) over the same distance, two different file lengths were obtained, 22 and 11 seconds, respectively, again except 10 km/h ICE Car, but not due to vehicle speed due to measurement distance (please see Footnote 8).

As a summary, **uncertainties** between trucks and car measurements due to setup, equipment and outdoor environment can be listed as:

- The used binaural heads were different in truck and car measurements which resulted in different head transfer functions.
- Measurement sites were different, truck measurements were held on Scania Test Track, while car measurements were done for EV car, at KTH campus and ICE Car in Uppsala. (soundscape properties, weather conditions due to measurement schedule, the measurements were performed at various times across different months, in March, April, and May)
- The Scania test track is well-defined and complies with ISO 10844:2021 standards, where truck measurements were conducted. In contrast, passenger car measurements were performed at the KTH campus and in Uppsala on public roads, where the surfaces are not well-defined or standardized.

3.1.2.2 Background Noise Recordings

Background noise recordings were carried out on March 8th and 9th, 2024 in Stockholm. Stereo sounds were recorded from different parts of the city, for at least 5 minutes at each location. The recordings were made with an H2n-Zoom audio recorder (with windshield), which was placed at a height of 1.6 m. Figure 3.3 presents a photo taken during one of the recordings. A calibrated sound level meter (B&K)

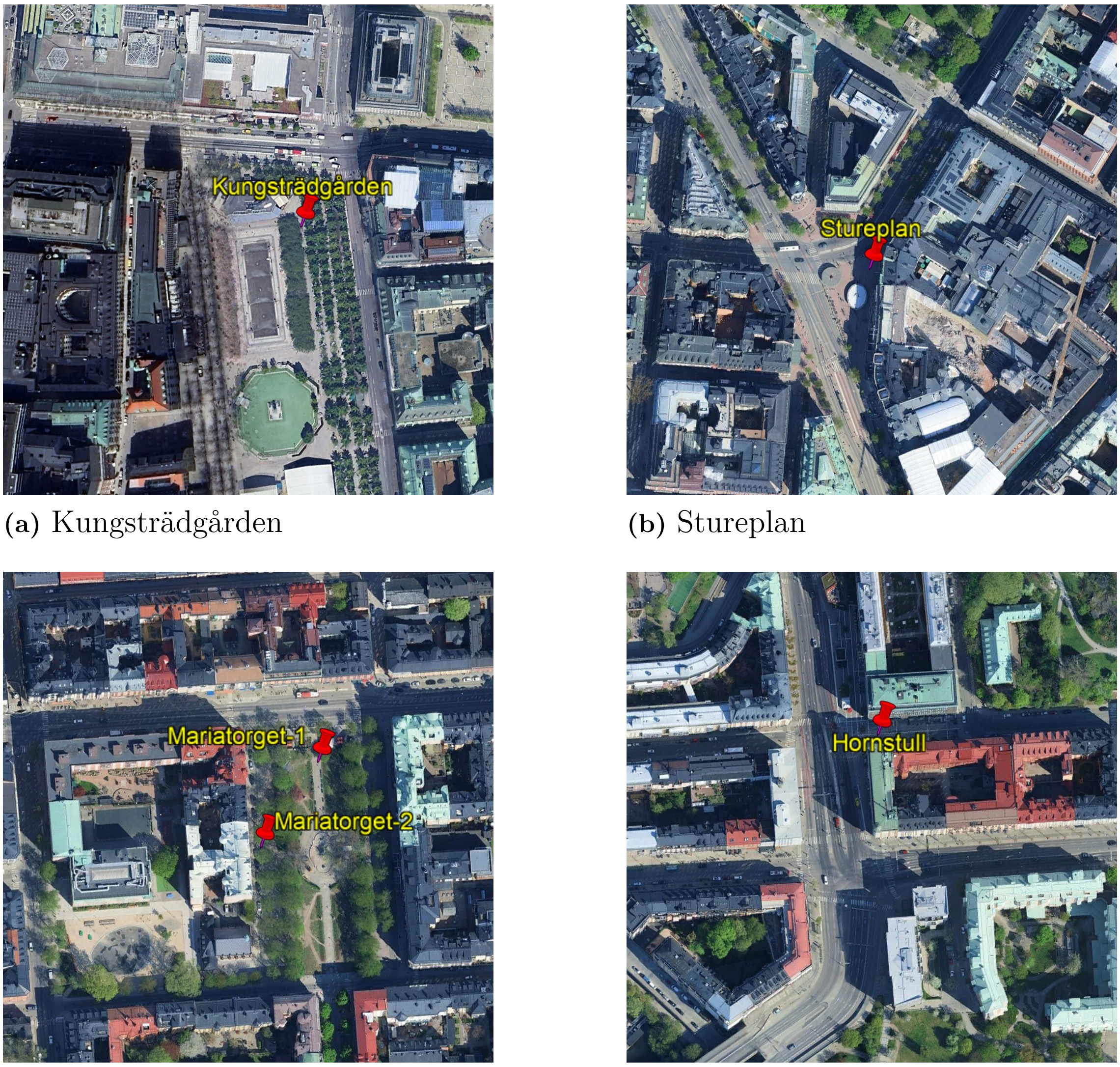
was also used during the recordings, and equivalent sound levels were measured and noted (between 55 dB(A) and 65 dB(A)). The weather was dry and there was no precipitation during these recordings.

Figure 3.3: Photo Taken During Recordings, Kungsträdgården, Stockholm.

Five of these recordings were selected as raw data. Figure 3.4 shows the selected locations. The main motivation behind choosing these locations was that they could adequately reflect the city's soundscape, including sounds, such as people walking, talking, laughing, traffic noise, birds chirping, music from cafes, restaurants and bars, strollers and dog barking.

The main criteria for preparing the sound files for the listening test was to maintain the representativeness of the city's soundscape, but at the same time, it should not be so distracting that it would disrupt the purpose of the test. Since background noises included traffic sounds, the sounds of passing vehicles in the background should not be heard so distinctly that they could be confused with the vehicle sounds aimed to be tested. In short, when participants were asked to detect a vehicle, the possibility of detecting a vehicle in the background noise had to be eliminated.

When preparing the sound files, the raw recordings selected for the tests were first exported from the H2n-Zoom microphone in 24-bit, 48 kHz WAV format and imported into Audacity Software. Considering the issues mentioned in the previous paragraph, the inappropriate parts of the raw data were trimmed and the appropriate parts were extracted and merged. As a result, 5 different 1-minute urban background sounds were obtained. The obtained sound files were high-pass filtered to minimize wind noise, as in the vehicle measurements, so frequencies lower than 30 Hz were removed from the files. In addition, as mentioned in the previous section, the passenger car sound files included too much bird noises compared to the truck files, so the background sounds were mixed with bird sounds to reduce the acoustic cue between them. Finally, in one file, the dog barking suddenly increased and was repeated several times. High-level and repetitive parts were removed from the file, but low-level dog barking sounds were mixed into this file to maintain its representation.



(a) Kungsträdgården **(b)** Stureplan **(c)** Mariatorget (two locations) **(d)** Hornstull

Figure 3.4: Selected Recording Locations in Stockholm (Source: Google, 2024).

The levels of the prepared files were adjusted by conducting a short test on a small group (5-6 subjects). The participants were made to listen to the audio files through headphones and were asked to determine the appropriate sound level for each file through computer audio volume under the assumption that they were walking in an urban environment. The answers for each file were averaged and the output level in the headphones was measured through audacity via binaural head and the sound levels were calculated accordingly. Consequently, background levels used in the test were varying equivalent single levels ranging between 57 and 62 dB(A) (Please see Appendix A for the equivalent levels at 1-second intervals and spectrograms of each background sound file).

3.2 Listening Test Procedure & Interface

As mentioned at the beginning of this chapter, the listening tests were conducted via a portable setup, which is shown in Figure 3.5, a computer (Lenovo ThinkPad) and headphones with active noise control (BOSE).

Figure 3.5: Listening Test Setup (Photos taken in Listening Studio at TMH, KTH.)

The test interface is provided by KTH. It was programmed via MATLAB App Designer[9], the design of the interface was kept as simple as possible not to create additional distraction to participants.

The interface includes two main parts, where they were titled "Classification" and "Detection& Classification", in line with the purposes of the listening test. In addition to these two parts, a "training" part was included at the beginning to familiarize the participants with the sounds they would encounter in the later parts of the test. Just before detailing the procedure followed during the tests and the introduction of the interface with the help of screenshots, Figure 3.6 shows the main steps of the conducted tests.

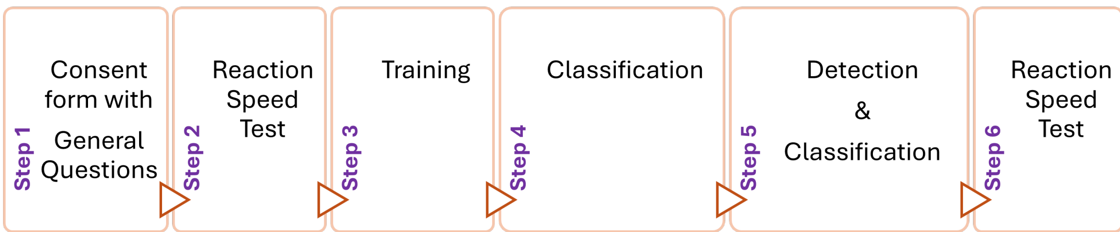


Figure 3.6: Main Steps of the Test Procedure.

[9]Information about this feature of MATLAB can be found in: https://se.mathworks.com/products/matlab/app-designer.html.

The following list provides explanations of the main procedure of the test illustrated in Figure 3.6:

1. Consent form with general questions: The test procedure began with participants signing a form that included the purpose of the study and general information, indicating that their participation was voluntary and that they could stop the test at any time without stating a reason. In addition, participants answered to 5 questions about whether they had a hearing impairment, their age, gender, familiarity with electric vehicle sounds, and sensitivity to sound.

2. Reaction test (before): Participants' reaction times to sound were assessed using an online test[10]. Thus, by doing this both individuals' reaction speeds and computer speed (the time from the moment the participants pressed the button until the data was saved through the test software) were taken into account.

3. Training Part: The training part was designed to familiarize the participants with the vehicle sounds that they would be tested within the later stages of the test. The sounds prepared for the test were presented in 4 categories: Electric car, electric truck, ICE car and ICE truck (see Figure 3.7). The participants were asked to listen to the sounds in each category at least five times, and no time limit was set. The vehicle sounds presented in 4 categories (how they were prepared is explained in Section 3.1.2.1) were presented without any additional background sounds and in a randomized manner.

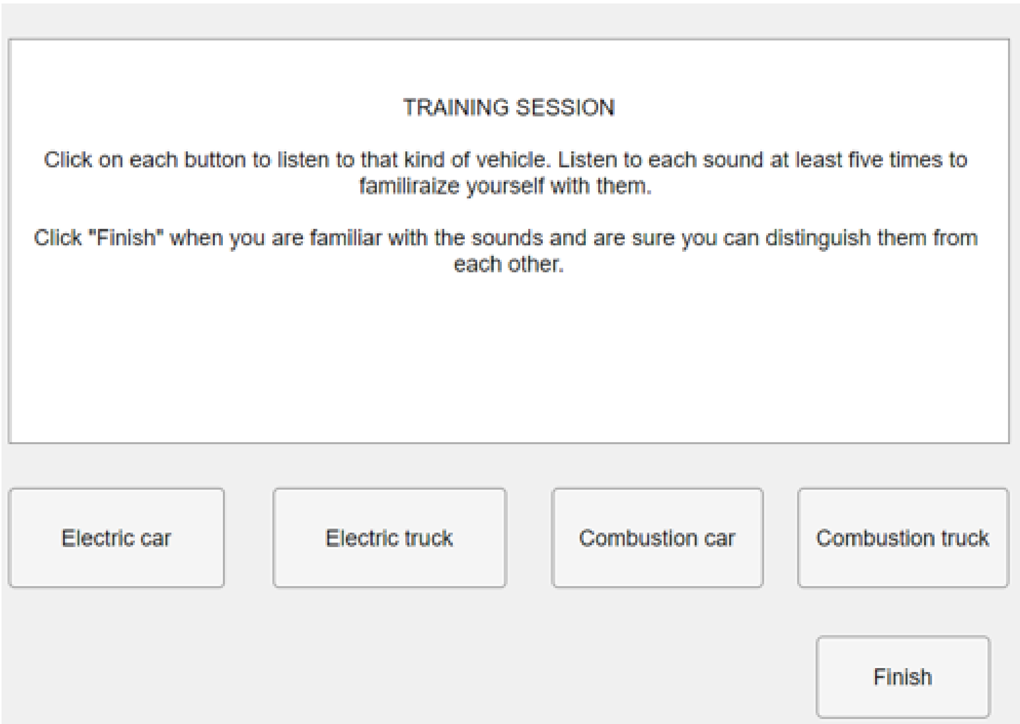


Figure 3.7: Training Part in the Test Interface.

[10]"What is Your Reaction Speed to Sound?" accessible via: https://playback.fm/audio-reaction-time.

4. Classification Part: In the classification part, the prepared vehicle sounds (listed in Table 3.1) were presented to the participants twice, and the participants were asked to respond to each sound they heard as belonging to a car or a truck. If the sound heard belonged to a truck, they were asked to press one of the blue buttons on the keyboard, and if it belonged to a car, they were asked to press one of the blue buttons (see Figure 3.5 for the coloured keyboard). In this part, 16 different vehicle sounds were tested and since each was asked twice, the participants responded to a total of 32 stimuli. The stimuli were presented in randomized order.

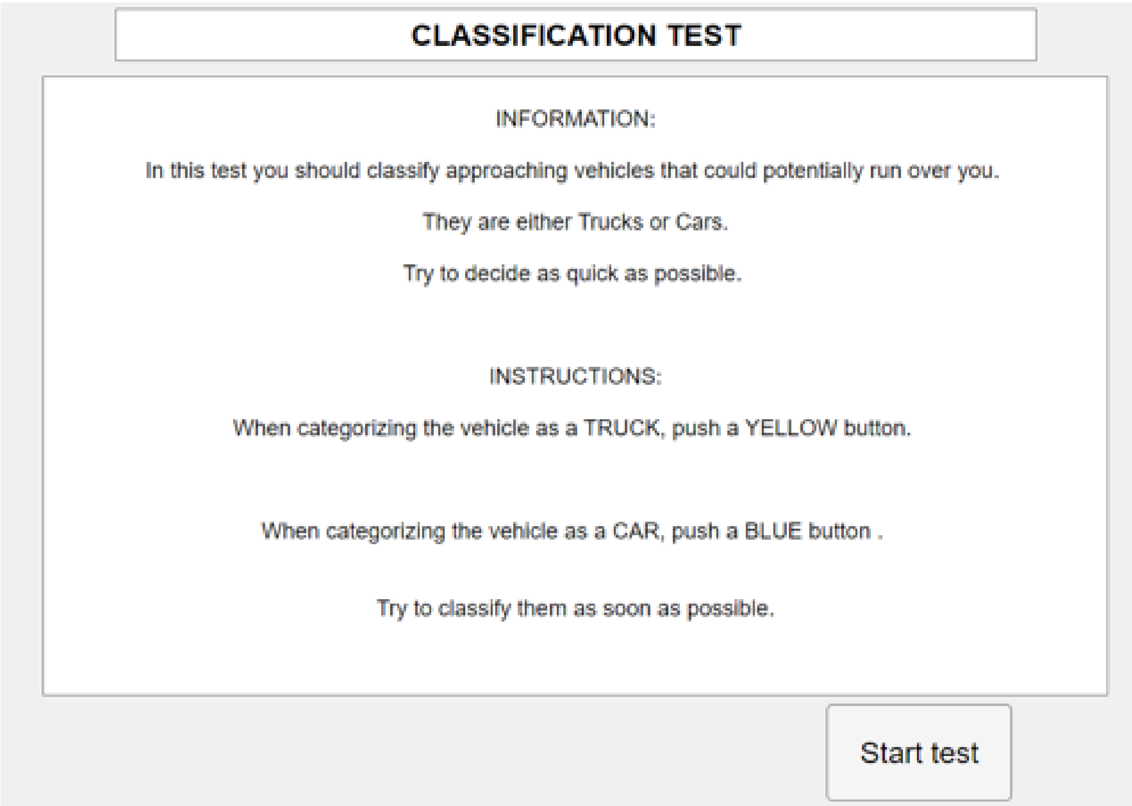


Figure 3.8: Classification Part in the Test Interface.

This part started with its training part, which was prepared to prepare the participants for the desired task. During both this training part and the actual test, the participants received feedback for each response they gave. As seen in Figure 3.9 if their answers were correct, they were presented with the text "correct" on the interface, if they were incorrect, they were presented with the text "incorrect". As can be seen in Figure 3.8, only responses categorized as car or truck were collected from the participants during the test. Sub-classifications including electric and ICE were not included in the test.

In addition, there was no time limit for the participants, but they were asked to answer as soon as possible and their classification times were recorded. After the stimulus ended, the participants started the next stimulus by pressing the space key, so they could respond before moving on to another stimulus.

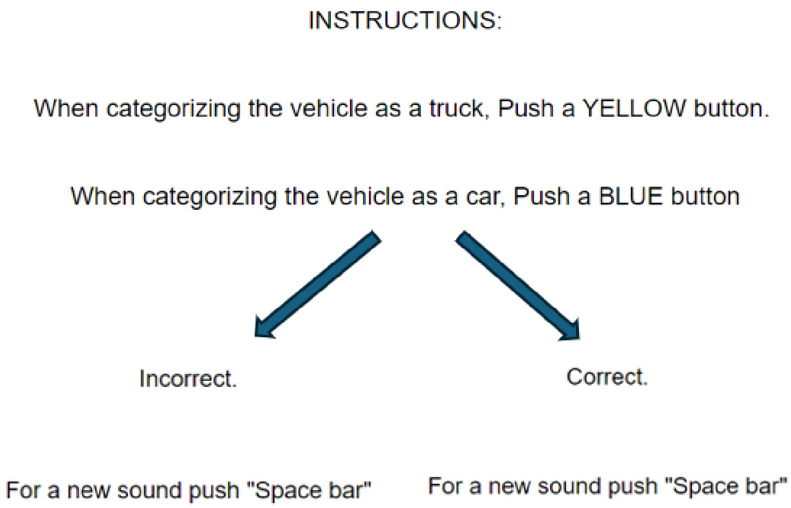


Figure 3.9: Classification Part Feedback the Test Interface.

5. Detection & Classification Part: This part of the test also included the training section, but here, unlike the classification part, only one sound clip was added for training purposes.

How the urban background noise files were prepared for the test was explained in detail in Section 3.1.2.2. During this task, vehicle sounds were presented while these prepared urban background sounds were playing. As stated earlier, each background sound was prepared as 1-minute duration. These files were presented 15 times in a random order, and vehicle sounds were placed in these files with different frequencies. Vehicle sound files and background noise files were not mixed or merged in the same file, which means vehicle sounds were played in the presence of background sound.

The order of the sounds of the presented vehicle sounds and their starting time were the same for each participant and each 1-min audio clip contained a maximum of 3 vehicle sounds. In other words, the participants heard 1, 2 or 3 vehicle sounds in the clips. However, two of the clips did not contain any vehicle sounds.

There is an important point to mention here, it was planned to include a total of 32 vehicle sound files (16 different vehicle sounds, with 2 repetitions). However, the placement of 2 sound files was forgotten by mistake. As a result, each participant heard the BEV Truck with modulated AVAS sound only once at both speeds (10 km/h and 20 km/h). In other words, a total of 30 sound files were tested in this section. The second repetitions of the modulated AVAS were not included in the test because they were forgotten. This situation did not cause a problem in the analysis phase since it was the same for each participant.

During this part, participants were asked to press the orange button (space bar at the keyboard see Figure 3.5) once they detected a vehicle, then immediately after, as soon as possible, they were asked the detected vehicle to classify again using one of the yellow buttons for a truck or blue buttons for a car (see Figure 3.10).

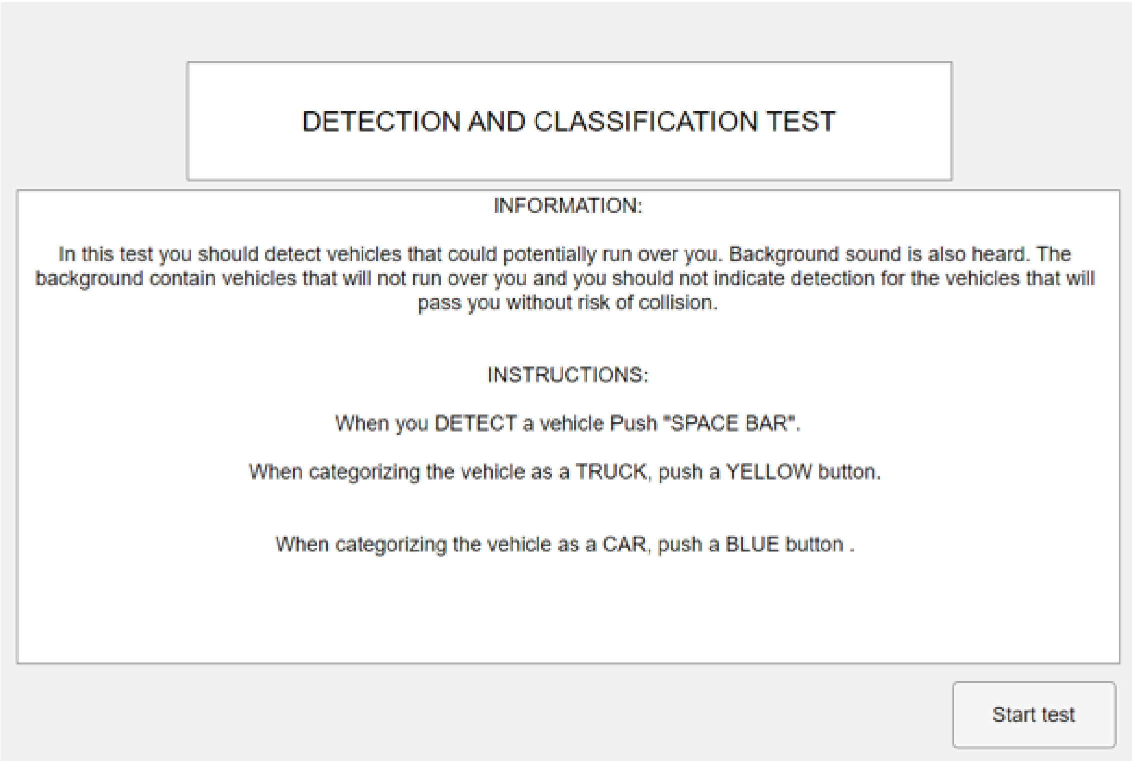


Figure 3.10: Detection & Classification Part in the Test Interface.

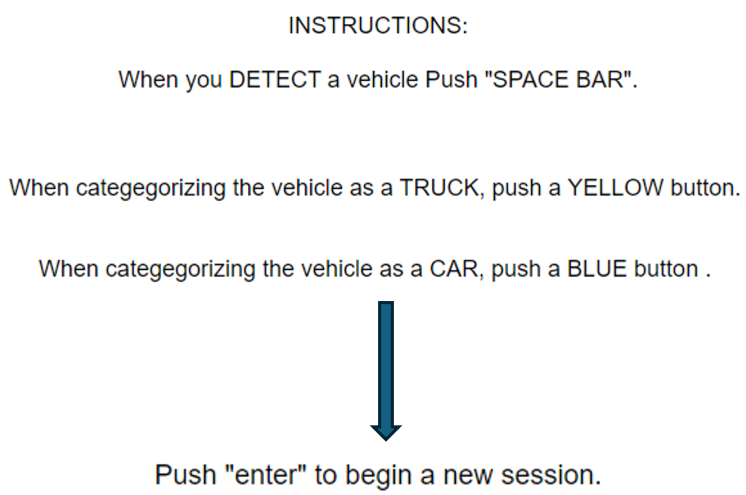


Figure 3.11: Detection Part in the Test Interface after Each Clip Ends.

Unlike the classification part, here participants did not receive any feedback, nothing happened when they pressed a button for detection or classification, and the sound clip did not pause once they pressed any button. Participants were tasked with a continuous process without any feedback during each clip. After one clip ended, they could continue with the following clip by pressing the enter button (see Figure 3.11).

6. Reaction test (after): The participants repeated the online test mentioned in Step 2 (see Footnote 10). These values (in ms), noted as before and after, were taken into account in the data analysis section by taking the average of each individual.

3.3 Listening Test Instructions

Although each test varied depending on how much time participants spent on the training section, the vast majority of tests lasted around 45 minutes to 1 hour.

In order to ensure consistency in the test, participants were not given any information outside of the written instruction context. Only written information was also expressed verbally. Each training session was supervised to answer possible questions regarding the process. Participants were left alone during the actual test sessions.

Followed Steps can be listed as:

- Participants were informed about the general purpose of the study. It was reported that their ability to classify and detect vehicle sounds would be assessed for safer urban areas. It was also emphasized that incorrect answers were as important as correct answers for the study.
- They were informed that the sound levels were adjusted and fixed, so there was no risk of hearing damage.
- Reaction speed tests were conducted and the result was noted.
- Both training vehicle sounds and classification part's training conducted, participant's question(s) were answered, within the written instruction (in the interface) context, if any.
- During the actual classification test, participants were alone. After completing (32 stimuli, were took a short break.
- Detection & Classification part was explained, and during its 1-minute training part, the participant was assisted if needed.
- During the actual Detection & Classification test, participants were alone. After completing 15 clips, 1 minute each, the test was completed.
- The Reaction test was repeated and response time was noted again.

4

Results & Discussion

The main goal of this chapter is to analyse the data obtained through listening tests and discuss the results in the context of the research questions formulated in the Introduction Chapter (see Section 1.3). As mentioned in more detail in the Methodology Chapter (see Section 3.2), the listening tests consist of "Classification" and "Detection & Classification" parts. As their names suggest, during the first part, the participants were asked to classify the approaching vehicle stimulus coming from whether trucks or cars, while during the second part, they were tasked with detecting approaching vehicles amidst continuous urban background noise and then classifying them as quickly as possible whether the sounds belonged to a truck or a car. Here, after providing the descriptive statistics of the participants, the chapter interprets the "Classification" and "Detection & Classification" parts' results, respectively. After presenting the study outcomes, the chapter ends with a discussion of the role of AVAS in future urban areas.

4.1 Descriptive Statistics of the Participants

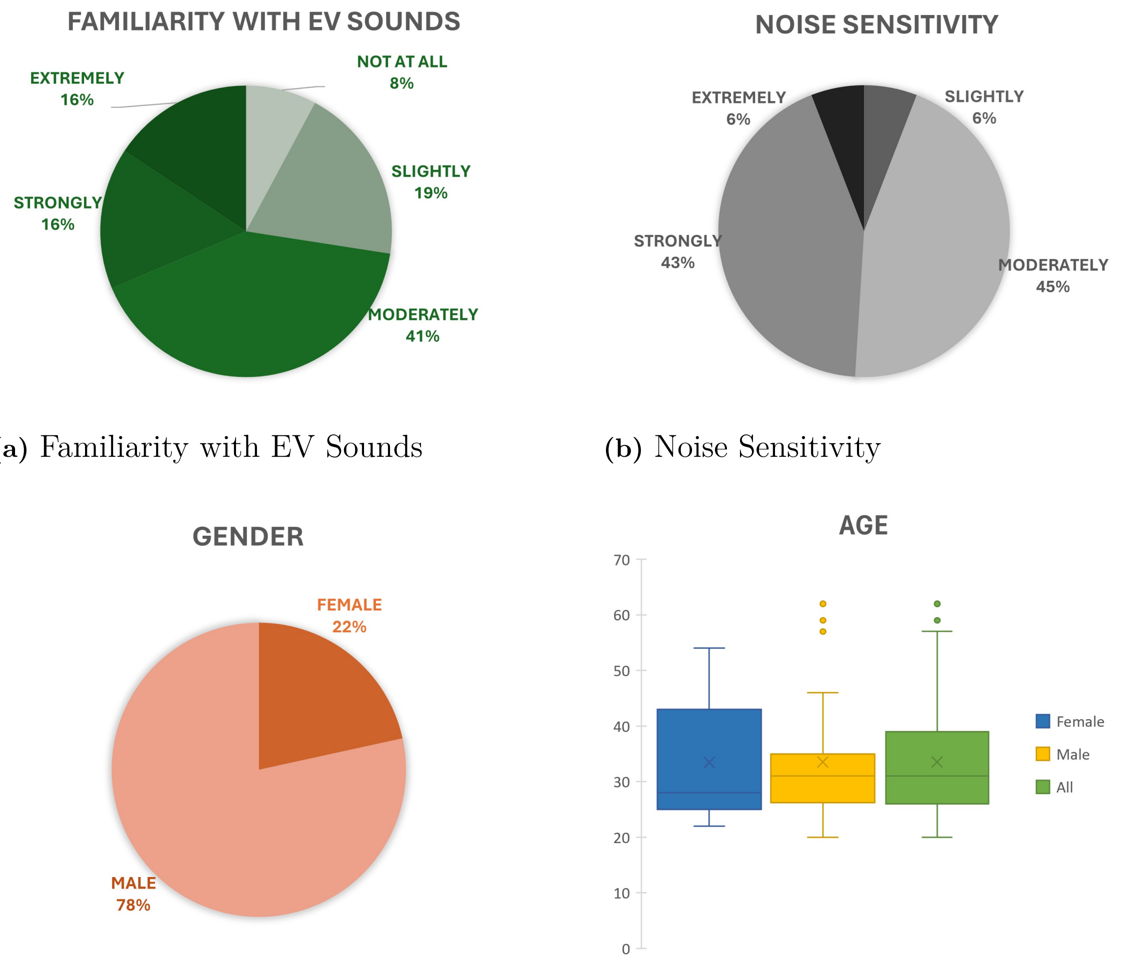
Before the listening test, participants answered five basic questions (see Appendix) regarding their hearing impairment, age, gender, familiarity with electric vehicle sounds, and noise sensitivity. Figure 4.1 summarizes the descriptive statistics of the participants based on these questions.

Out of 51 participants in the listening tests, 40 were male (78 %) and 11 were female (22 %). The median age for female participants was 28, with a mean age of 33 and a standard deviation of 10, indicating a varied age range. For male participants, the median age was 31, with a mean age of 34 and a standard deviation of 10, also indicating a varied age range. Overall, the median age was 31, the mean age was 34, and the standard deviation was 10, showing that the ages of participants, regardless of gender, are spread out similarly.

Only 2 participants (4 %) reported having a hearing impairment. These participants' results were consistent with the overall data and did not appear as outliers, thus they were included in the analysis.

In the question assessing participants' familiarity with EV sounds, the data revealed that 41% of respondents were moderately familiar with these sounds. A combined 27% of participants indicated low familiarity, either not at all or slightly familiar. This suggests that while a significant portion of the participants have some level of familiarity, there is still a notable group with limited exposure.

Additionally, 32% of participants reported strong to extreme familiarity with EV sounds, highlighting a substantial level of high familiarity among the respondents. Overall, the survey indicates a varied level of awareness and familiarity with EV sounds, with a majority having at least moderate familiarity and a significant portion demonstrating high familiarity.



(a) Familiarity with EV Sounds

(b) Noise Sensitivity

(c) Gender

(d) Age

Figure 4.1: Descriptive Statistics of the Participants.

Participants rated their sensitivity as "Not at all," "Slightly," "Moderately," "Strongly," or "Extremely." The results indicated that 51 % of participants have low sensitivity (combining "Not at all," "Slightly," and "Moderately"), while 49 % have high sensitivity (combining "Strongly" and "Extremely"). The largest single category was

"Moderately" sensitive at 45 %, suggesting that most participants experience some level of noise sensitivity, but not to an extreme degree.

In addition, participants' reaction times to sound were assessed using an online test[1] conducted both before and after the listening test. Figure 4.2 illustrates each participant's reaction times to sound before and after the tests, while Figure 4.3 shows the overall changes regarding reaction speeds and times.

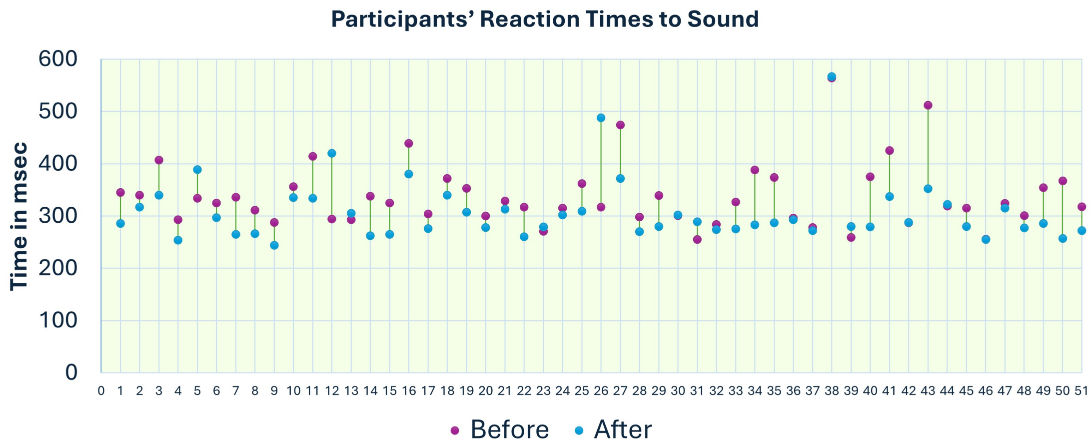
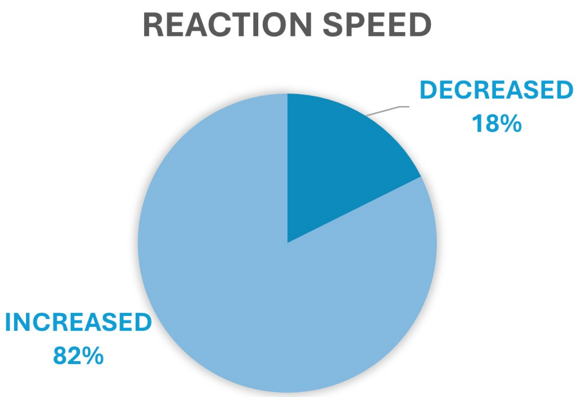
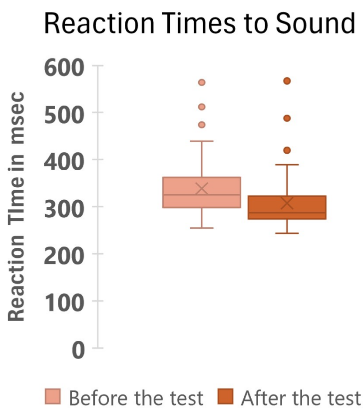


Figure 4.2: Each participant's reaction times to sound before and after the listening test.



(a) Changes in reaction speeds before & after



(b) Changes in reaction times before & after

Figure 4.3: Changes in participants' reaction speeds and times to sound before and after the listening test.

Before the listening tests, the mean reaction time was 339 ms, the median was 325 ms, and the standard deviation was 61 ms. After the tests, the mean reaction time

[1]"What is Your Reaction Speed to Sound?" accessible via: https://playback.fm/audio-reaction-time.

decreased to 307 ms, the median was 287 ms, and the standard deviation was 58 ms. In particular, 82% of the participants showed improved performance, indicated by a decrease in reaction time and an increase in reaction speed. Individual reaction speeds were taken into account when interpreting the rest of the study, i.e. the mean value of each participant's before and after reaction times was considered.

4.2 Classification Results

The classification results aim to address the following research question:

"How accurately can pedestrians classify sounds as coming from cars or trucks under different conditions?"

Here, different conditions refer to classification time settings. In the classification part, participants identified whether the vehicle sound they heard belonged to a truck or a car. There was no time limit for their responses, allowing them to answer even after the stimulus had ended. On the other hand, the timing of their classifications was recorded for analysis purposes. By organizing their answers under three specific conditions, the analysis aims to answer the following sub-questions:

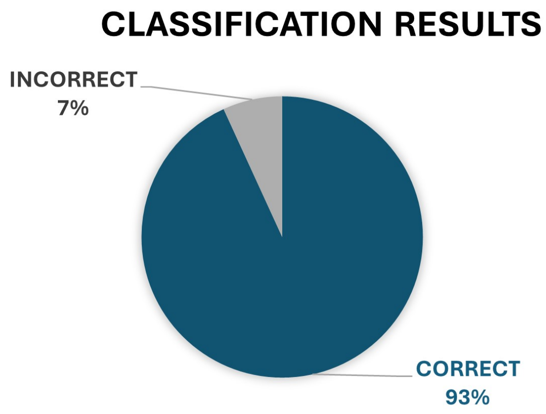
A. Can pedestrians accurately classify vehicles when there is no time constraint?
B. Can pedestrians accurately classify vehicles within stimuli duration?
C. Can pedestrians accurately classify vehicle sounds at safe distances?

Before delving into these questions, it is worth noting that three participants' results were excluded from the analysis due to improper recording of their classification times during the tests. Consequently, the classification analysis included 48 subjects, 11 females and 37 males.

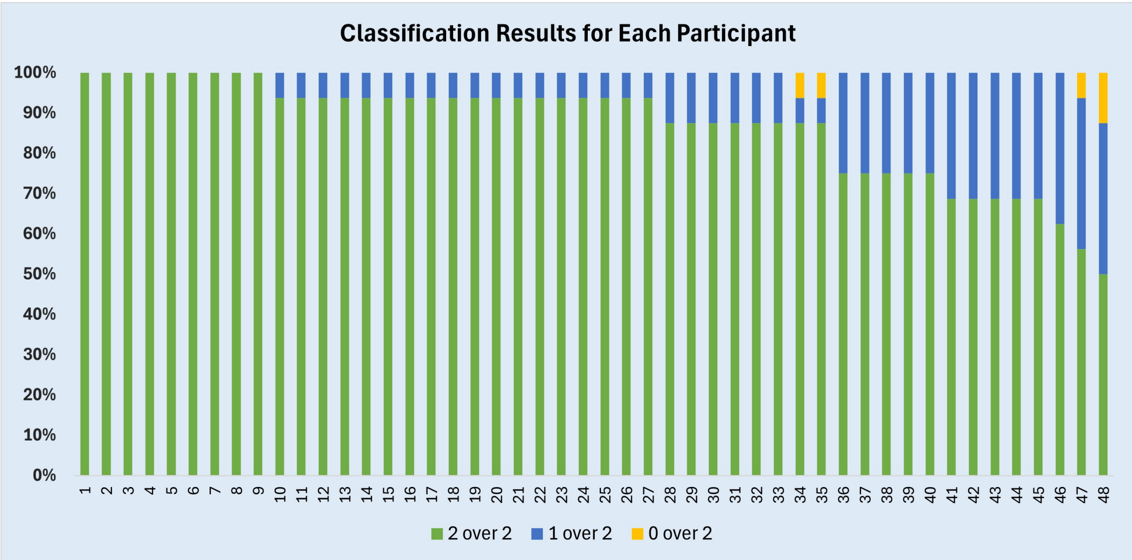
4.2.1 Case A: Can pedestrians accurately classify vehicles when there is no time constraint?

During the classification part, participants could classify the sounds at any time, even after the stimulus had ended. Since there is no time constraint for the classification in this sub-question (Case A), all collected classification data are included in the calculations. Figure 4.4 provides a summary of all the results for this case.

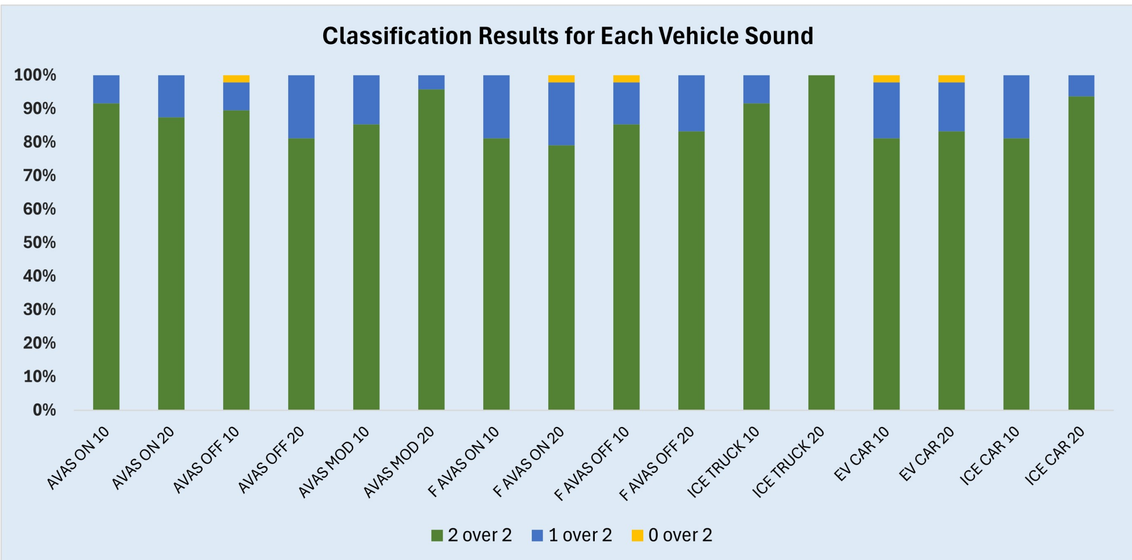
As a quick reminder, in the classification part, participants were tested with 8 different vehicle sounds at 2 different vehicle speeds, resulting in a total of 16 unique vehicle sounds. Each vehicle sound was presented twice, leading to a total of 32 stimuli. In the mid and bottom figures, green indicates "2 over 2," meaning the participant correctly classified that vehicle sound both times. Blue indicates "1 over 2," meaning the participant correctly classified the sound once but not the other time. Yellow indicates that the participant could not correctly classify the vehicle sound either time.



(a) Classification Results without Time Constraints



(b) Classification results for each participant



(c) Classification results for each vehicle

Figure 4.4: Classification results for Case A.

As seen in Figure 4.4a, 93% of the results were correctly classified, while 7% were incorrectly classified. Figure 4.4b shows the classification accuracy of each participant. Out of the 48 participants, 9 achieved 100% correct classifications. The minimum classification accuracy recorded was 68.75%. This summary highlights the overall high performance, with most participants achieving near-perfect results and a few showing slightly lower accuracy.

Figure 4.4c shows the classification results for each vehicle sound. The classification results for this case (without time constraints) show a high overall accuracy, with most vehicle sounds being correctly classified over 90% of the time. The highest accuracy was observed with ICE TRUCK 20 at 100% correct classifications, indicating that this sound was the easiest for participants to identify correctly. On the other hand, F AVAS ON 20 had the lowest accuracy at 88.54%, suggesting it was more challenging for participants to classify correctly. More specific comparisons based on the results can be summarized as follows:

- 10 km/h vs 20 km/h: Vehicle sounds at higher speeds (20 km/h) generally had slightly lower accuracy compared to those at lower speeds (10 km/h). This trend is consistent across most vehicle sounds, suggesting that stimuli duration may have an impact on the participant's ability to classify the sounds correctly.

- AVAS on vs AVAS off: The data indicates that with AVAS ON, the correct classification rates are slightly higher at both 10 km/h and 20 km/h compared to AVAS OFF. This suggests that the AVAS system may provide additional auditory cues that help participants classify the sounds more accurately when there is no time constraint.

- BEV Trucks vs ICE Trucks: ICE trucks outperform BEV trucks with AVAS ON in terms of accuracy at both speeds. At speed 10, ICE truck achieve 95.83% accuracy, while BEV trucks range from 90.63% to 95.83%. At speed 20, ICE trucks reach 100% accuracy, whereas BEV trucks range from 88.54% to 97.92%. Among BEV trucks, AVAS MOD 20 shows the highest accuracy (97.92%).

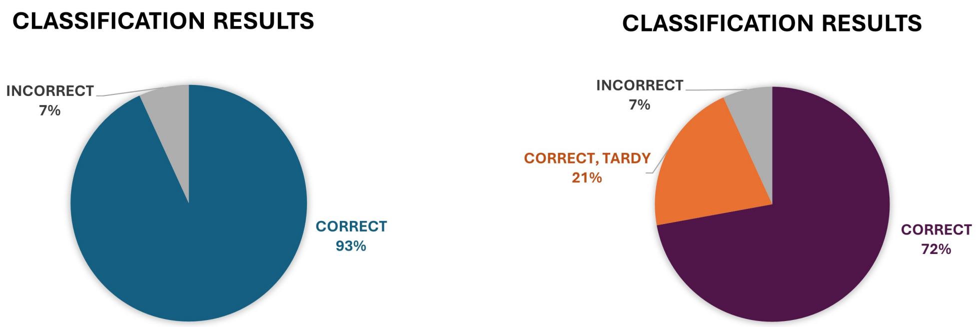
- BEV Trucks vs EV Car: BEV trucks with AVAS ON, outperform EV cars in terms of accuracy at both speeds. At speed 10, BEV trucks achieve up to 95.83% accuracy, while EV cars reach 89.58%. At speed 20, BEV trucks with modulated AVAS achieve the highest accuracy of 97.92%, compared to 90.63% for EV car.

- Effect of Tonal Components: As a quick note, here F AVAS refers that tonal components of BEV Truck were filtered, decreased 12 dB. This indicates that AVAS ON performs slightly better than F AVAS ON at both speeds, with a more significant advantage at 20 km/h. Indicating that maybe tonal components of BEV Truck were used as an audio clue while participants were classifying.

- AVAS vs Modulated AVAS: Modulated AVAS slightly outperforms at 20 km/h, with lower error percentages, while for 10 km/h is the opposite.

4.2.2 Case B: Can pedestrians accurately classify vehicles within stimuli duration?

To address this sub-question, correct answers were categorized into two groups based on the timing of participants' classifications. In other words, responses given after the stimulus ended were considered late. Figure 4.5b provides a summary of the overall results for this case. Figure 4.5a, which is added here for comparison reasons, is a repetition of Figure 4.4a showing Case A results.



(a) Classification Results without Time Constraints

(b) Classification Results when stimulus times are considered

Figure 4.5: Comparison of Classification Results for Case A and Case B.

The introduction of time constraints leads to a decrease in the correct classification rate from 93% to 72%. In Case B, 21% of the responses are tardy, meaning they were correctly classified but not made within the stimuli duration.

In the following step, Figure 4.6 compares Case A and Case B, showing how the correct classification percentages for each vehicle sound change when stimuli durations are considered. The analysis of the percentage differences between Case A and Case B reveals a consistent trend where Case B correct classification percentages are lower across most vehicle sounds, except AVAS off 10 km/h and filtered AVAS on 10 km/h, where their percentages remained the same. Moreover, several vehicle sounds experienced a notable drop in Case B compared to Case A. To illustrate, vehicle sounds like AVAS on 20 km/h, filtered AVAS off 20 km/h, and EV car 20 km/h saw significant decreases of 59.4%, 58.4%, and 54.1%, respectively. Moderate declines were observed in vehicle sounds such as modulated AVAS 20 km/h, ICE Truck 20 km/h, and ICE Car 20 km/h.

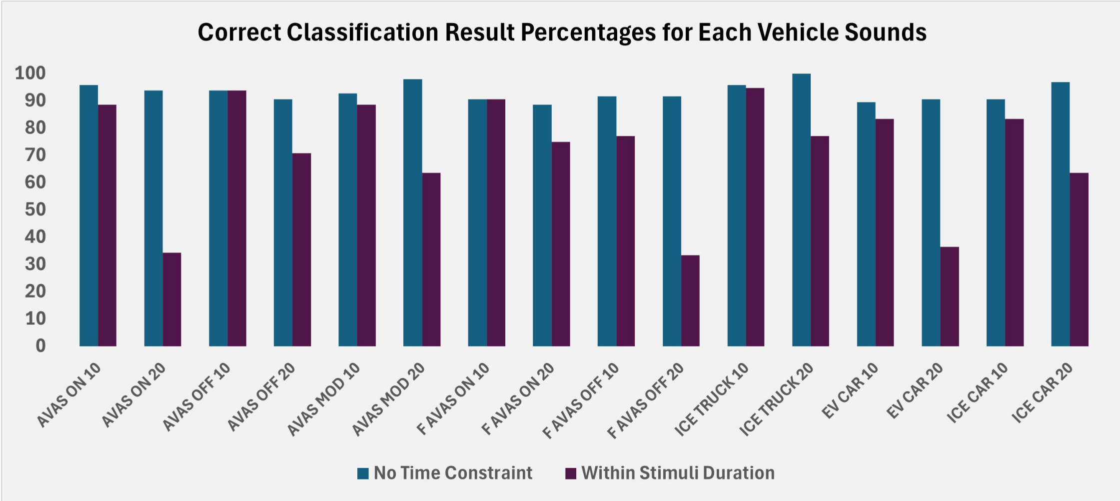


Figure 4.6: Correct Classification Result Percentages for each Vehicle Sound for Case A and B.

More spesific comparisons derived from Figure 4.6 can be outlined as follows:

- 10 km/h vs 20 km/h: As discussed in the previous section, in Case A, correct responses are slightly lower at 20 km/h compared to 10 km/h, except for modulated AVAS 20 km/h and ICE Truck 20 km/h, which show higher values. In Case B, the decrease is more pronounced, and several vehicle sounds, such as AVAS on 20 km/h and filtered AVAS off 20 km/h, are significantly lower at 20 km/h. This comparison shows that correct classification responses tend to decrease at 20 km/h. Considering the fact that measurements were performed at the same distance, 50 m from the observer, stimulus duration of 20 km/h vehicle sounds were half of those 10 km/h ones. This may suggesting that shorter stimuli durations become more challenging for participants to classify the vehicle sounds or at 20 km/h, EV car sound and BEV Truck sounds were harder to distinguish.

- AVAS on vs AVAS off: In Case B, AVAS seems to reduce classification accuracy, especially at 20 km/h. This could indicate that AVAS sound does not provide enough audio cues to differentiate from a car sound if a decision is made within stimuli duration.

- BEV Trucks vs ICE Trucks: Within the stimuli duration, ICE trucks maintain a higher accuracy of 85.94% compared to BEV trucks at 77.08%. This suggests that participants found it easier to classify ICE truck sounds, possibly due to more distinct and recognizable auditory features compared to BEV trucks.

- BEV Trucks vs EV Car: Within the stimuli duration, BEV trucks maintain a higher accuracy of 68.75% compared to EV cars at 59.90%. Although it seems this suggests that the presence of AVAS in BEV trucks provides additional auditory cues that help participants classify the sounds more accurately, compared to EV cars, considering the participants' options were only truck or car as a response, sum of the wrong answers from BEV Trucks and EV car together, can not be underestimated. All the wrong answers for BEV Trucks and EV car can be seen as a sign that EV's AVAS sound and BEV trucks' AVAS sounds are not distinguishable enough.

- Effect of Tonal Components: Unlike the results of Case A, in Case B, filtering the tonal components of the BEV truck made it more accurately classified by participants, particularly at 20 km/h. While the BEV truck with AVAS was classified 34.38%, its filtered version significantly outperformed, 75% correctly classified. Maybe due to AVAS sound was more audible with decreasing the tonal components of the BEV Truck, consequently ensuring participants classified it earlier.

- AVAS vs Modulated AVAS: In Case B, both AVAS and modulated AVAS at 10 km/h have the same accuracy (88.54%). On the other hand, at 20 km/h, modulated AVAS (63.54%) far much higher correctly classified than AVAS (34.38%). This suggests that also considering Case A results, modulated AVAS provides more effective auditory cues for classification, particularly at 20 km/h.

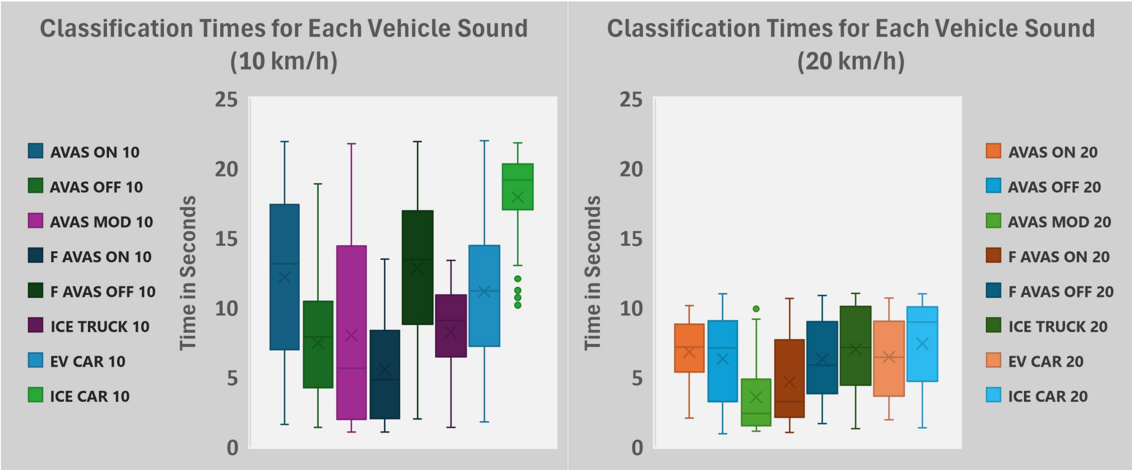
4.2.3 Case C: Can pedestrians accurately classify vehicle sounds at safe distances?

In the previous sections, 4.2.1 and 4.2.2, classification results addressed the cases without time constraints and within stimuli duration, respectively. As a further step, this section aims to answer if classified vehicle sounds within stimulus duration were classified at safe distances by participants.

Figure 4.7 shows participants' classification times for 10 and 20 km/h vehicles separately[2]. Here zero refers to when the stimuli start and correspond to 50 m from the observer (binaural head), while 22 seconds (for 10 km/h) and 11 seconds (for 20 km/h) refer to when the stimuli end, approximately 10 m away from the observer after the vehicle passed, respectively. This figure does not show classification responses after the stimulus ends but displays classification results within the stimuli durations. Therefore, as seen in the figure, the maximum classification times for 10 and 20 km/h are 22 and 11 seconds, respectively. Participants' classification times were converted to distances[3] to enable a clearer comparison. Figure 4.8 shows the distances corresponding to classification times depicted in Figure 4.7.

[2]As explained in the Methodology Chapter, measurements were performed from a distance of 50 m from the observer (binaural head) and continued approximately 10 m away after passing the observer, covering a total distance of 60 m. This, inherently, resulted in obtaining different stimulus durations for 10 km/h and 20 km/h: 22 seconds and 11 seconds, respectively.

[3]To illustrate if it is supposed that a stimulus is classified at fifth seconds, this response for 10 km/h (2.78 m/s) corresponds to 13.9 m away from the starting point of the measurement and 36.1 m away from the observer, since the distance between the starting point and the observer is 50 m; and for 20 km/h (5.56 m/s) corresponds to 27.8 m away from the starting point and 22.2 m from the observer.



(a) Vehicle Speed: 10 km/h (b) Vehicle Speed: 20 km/h

Figure 4.7: Classification Times within Stimuli Durations for each Vehicle Sound.

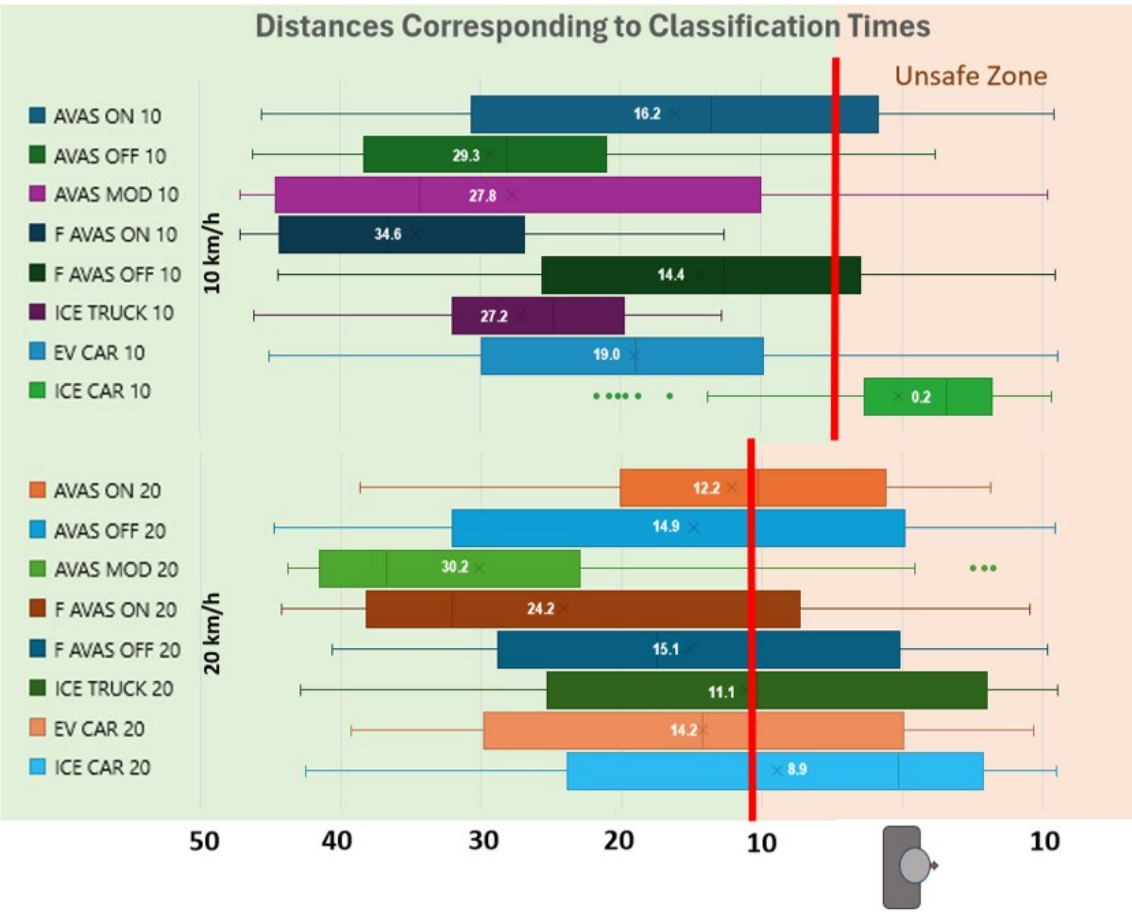


Figure 4.8: Distances Corresponding to Classification Times.

In Figure 4.8 the horizontal axis shows the distances in meters. The observer is positioned at the zero point on this axis, standing parallel to the road. Vehicles are approaching from 50 meters away behind the observer and continue for 10 meters after passing the observer. Each vehicle sound was represented in different colours, and the written numbers on each vehicle refer to mean classification distances and show the distance from the observer. The top of the figure shows the 10 km/h vehicle sounds, while the bottom depicts their 20 km/h versions. The red lines show the border of the unsafe zone[4], calculated as 11 m for 20 km/h vehicles and 5 m for 10 km/h vehicles.

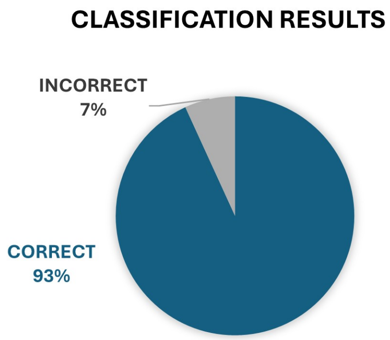
As seen in the figure, while the vast majority of vehicles with a speed of 10 km/h are classified in the safe zone, the same cannot be said for vehicles with a speed of 20 km/h. The vehicles that were classified earliest were filtered AVAS on and modulated AVAS. On the other hand, in an unexpected case where AVAS was not active, the vehicle was classified earlier according to the state where AVAS was active. Based on this result, the following comments can be made: the sound produced by the BEV Truck may be masked by the AVAS sound. In other words, the sounds that participants can use as clues (most likely tonal components of the truck) may have lost their clarity. Similarly, the better performance of the BEV truck with filtered tonal components than the normal one can be explained in the same way, this time in the opposite way, since the tonal components do not mask the AVAS sound, the AVAS sound becomes more audible to the participants.

Enhanced understanding is obtained by comparing this case with those previously presented. Figure 4.9 compare the results for all the classification cases. While Figure 4.9a, 4.9b, and 4.9c illustrate the overall results, Figure 4.9d displays correct classification percentages for each vehicle sound. When the safe distances are considered, classification results drastically change comparing the previous cases, in Case C, only 50% of responses were correct and in the safe zone. Correct classification percentages for each vehicle have noteworthy variability, ranging between 16.67% to 94.79%. Based on Figure 4.9d, the following comparisons can be made by excluding the Ice car results (as it provides an outlier for this case):

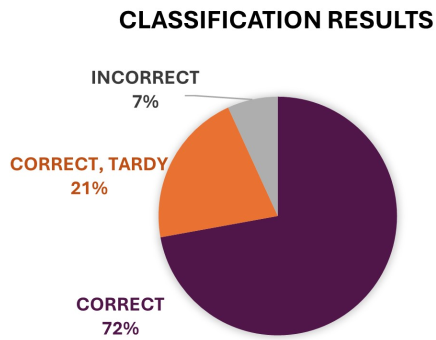
- 10 km/h vs 20 km/h: Classification responses for 20 km/h were more consistent, ranging from 16.67% to 37.5%, and notably lower compared to 10 km/h vehicle sounds, which the majority of them classified correctly at safe distances with percentages ranging from 53.13 to 94.79.

- AVAS on vs AVAS off: AVAS off mode provided more stable and higher performance in this case, as discussed earlier probably due to the masking effect of AVAS sound on tonal components of the BEV truck.

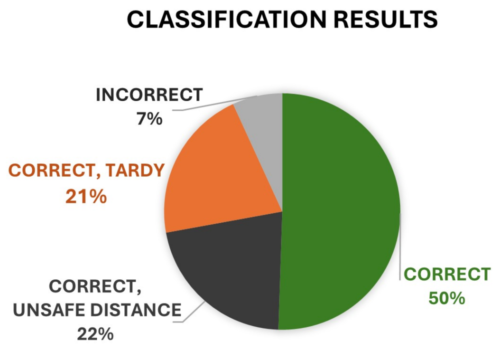
[4]The borders of the unsafe zone were decided through stopping distances of trucks with 10 km/h and 20 km/h constant speeds. Stopping distances were calculated based on these assumptions: road surface is asphalt and in dry conditions which gives $6\,\mathrm{m/s^2}$ acceleration (in a conservative scenario), reaction time for the driver is 1 second and reaction time for the system is 0.5 seconds (in the worst case).



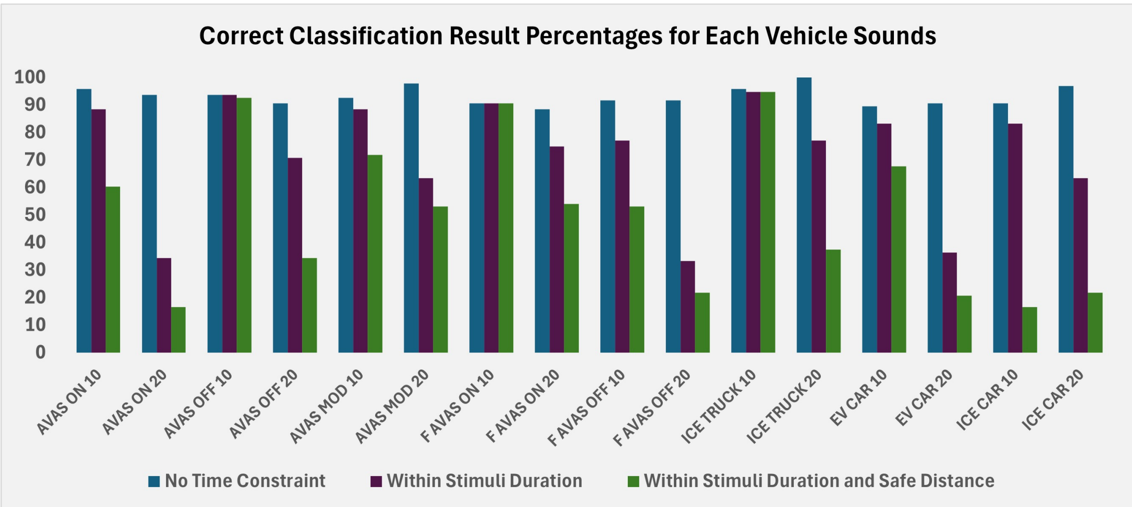
(a) Without Time Constraints



(b) Within Stimulus Times



(c) Within Safe Distances



(d) Correct Classification Result Percentages for Each Vehicle Sounds

Figure 4.9: Comparison of Classification Results for Case A, B and C.

- BEV Trucks vs ICE Truck: The performance of AVAS in active mode for BEV trucks varied significantly from 16.67% to 94.79%. In contrast, the correct classification rate of the ICE truck at 20 km/h was surprisingly low (37.5%). This low rate may not be because participants were unsure whether the sound belonged to an ICE truck, maybe they were sure and did not feel the urgency to classify it quickly.

- BEV Trucks vs EV Car: When comparing the results with AVAS on mode for BEV trucks, the results for BEV trucks showed wide variability at 20 km/h. Modulated AVAS and the BEV truck with filtered tonal components outperformed both the EV car at 20 km/h and AVAS active mode. On the other hand, the low performance of AVAS on mode (16.67%) and the EV car (20.82%) suggests that their sounds are not distinguishable enough at safe distances.

- Effect of Tonal Components: Like in Case B, filtering the tonal components of the BEV truck made it more accurately classified by participants, but this time not only at 20 km/h but also at 10 km/h significantly differed. While the BEV truck with AVAS was correctly classified at 10 and 20 km/h, 60.41% and 16.67%, respectively; its filtered version significantly outperformed, 90.63% and 54.17%, suggesting that it was more audible to participants.

- AVAS vs Modulated AVAS: For this case, the modulated version of AVAS provides more consistent and higher performance in both vehicle speeds, but particularly at 20 km/h (like in Case B).

4.2.4 Summary of Classification Part Outcomes

During the classification process, participants were asked to respond whether the sound they heard belonged to a car or a truck "as soon as possible". No time limit was set, and the tests were not conducted in 3 separate phases. Instead, the participants' classification times were saved and the data were examined in 3 phases during the analysis.

In the first phase (Case A), all responses were considered regardless of time, in the second (Case B), the stimulus durations were considered and only the responses from participants answered during the stimulus were focused on. In the third case (Case C), safe distances were considered and therefore responses within safe distances were examined. When considering all the classification results in different cases, it becomes essential to emphasize several outcomes. ICE Trucks consistently performed best, especially at 10 km/h, where, as expected, participants classified them more easily. The BEV truck with modulated AVAS and filtered tonal components generally outperformed its unmodulated and unfiltered counterparts, suggesting that these modifications provided participants with more clues for classification. Moreover, the correct classification rates of BEV Trucks varied significantly when safe distances were considered. Based on this, it can be concluded that participants had more difficulty distinguishing truck sounds from car sounds when classifying vehicles at a distance. In addition, although more stable, EV Cars generally had lower scores than BEV Trucks and ICE Trucks, indicating that participants were often in a dilemma between identifying a car or a truck.

To summarize, vehicle type, speed, and the presence of modulation of AVAS and filtering effects (tonal components of the BEV truck) played an important role in the classification accuracy.

4.3 Detection Results

The detection results aim to address the following research question:

"How accurately can pedestrians detect and classify vehicles amidst continuous urban background noise?"

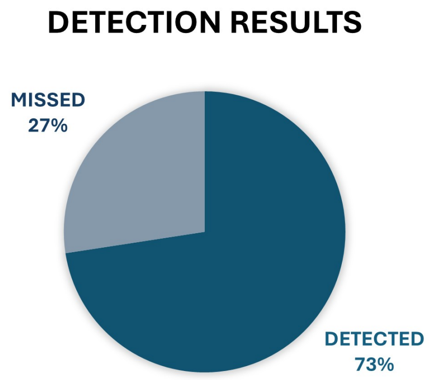
In the detection part, participants first detected an approaching vehicle within continuous urban background noise. Then they identified whether the vehicle sound they heard belonged to a truck or a car (for more details about the detection part please refer to Section 3.2). By organizing their answers under four situations, the analysis aims to answer the following sub-questions:

A. Can pedestrians detect vehicles amidst continuous urban background noise?
B. Can pedestrians accurately classify the detected vehicles?
C. Can pedestrians detect vehicles at safe distances?
D. Can pedestrians accurately classify the vehicles that are detected at a safe distance?

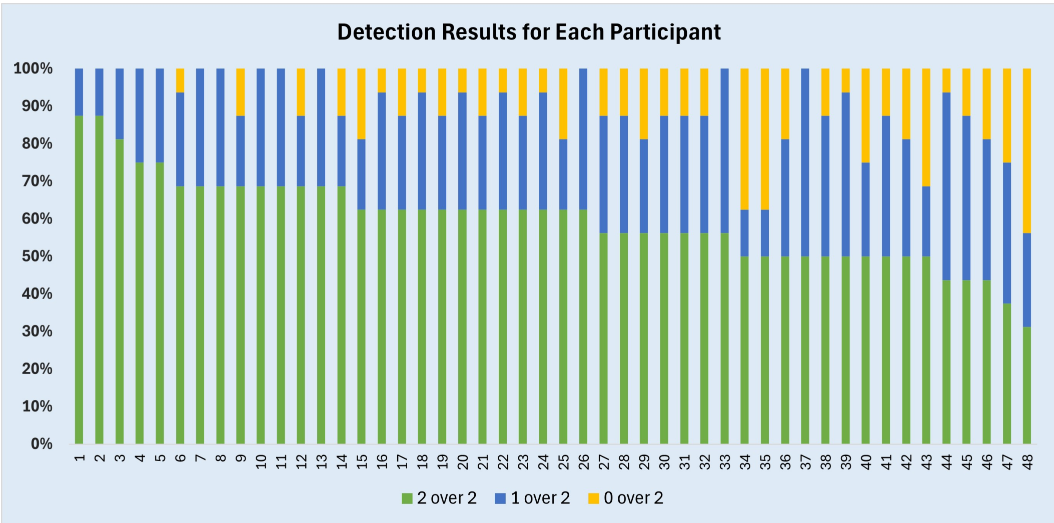
Before addressing these questions, it is worth noting that three participants' results were excluded from the analysis due to a miscommunication about the test instructions. As a result, 48 subjects' results, 10 females and 38 males were analysed.

4.3.1 Case A: Can pedestrians detect vehicles amidst continuous urban background noise?

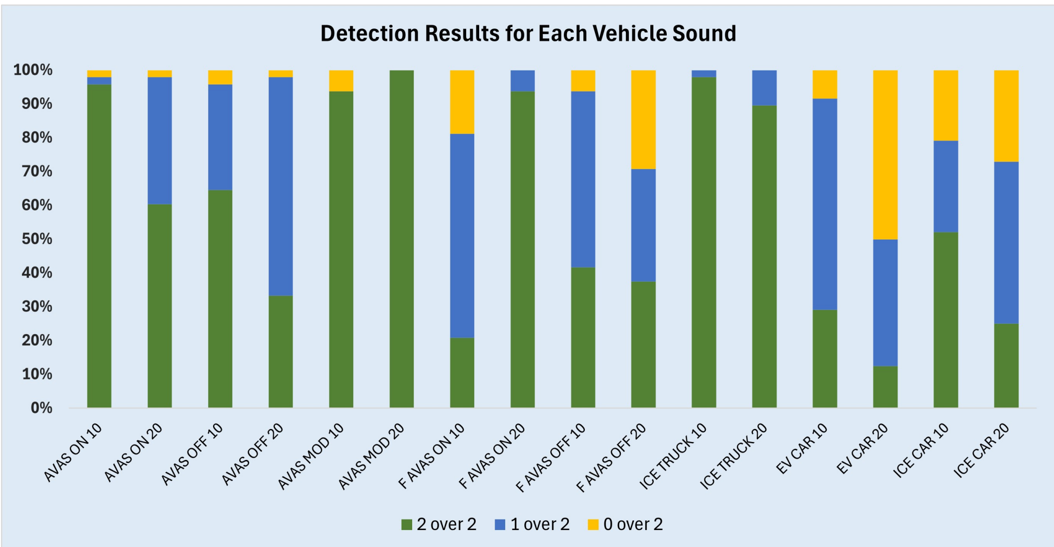
As a quick reminder, measurements included a total of 60 m distance, starting 50 m away from the binaural head and continuing 10 m after passing it, as a result, the duration of the measurement files was 22 seconds for 10 km/h while 11 seconds for 20 km/h. Figure 4.10 summarizes detection results for this 60-meter distance segment, safe distances are not considered for this case (it will be considered in cases C and D). In other words, it shows all the detection results even if they were detected after passing the binaural head, i.e. in the last 10-meter segment. While Figure 4.10a shows overall detection results, Figures 4.10b and 4.10c show the detection results for each participant and each vehicle, respectively.



(a) Overall Detection Results.



(b) Detection results for each participant.



(c) Detection Results for Each Vehicle Sound.

Figure 4.10: Detection Results.

As mentioned earlier, each vehicle sound was presented twice in the tests. In Figures 4.10b and 4.10c, green indicates “2 over 2,” meaning the participant detected that vehicle sound both times. Blue indicates “1 over 2,” meaning the participant detected the sound once and missed it once. Yellow indicates that the participant could not detect the vehicle sound at either time. However, as explained in Section 3.2, The second repetitions of the modulated AVAS were forgotten. So here, for modulated AVAS 10 km/h and 20 km/h green shows detected and yellow shows undetected.

Overall results, presented in Figure 4.10a, revealed that 73% of the vehicles were detected and 27% missed. Looking into each participant’s results in Figure 4.10b, 13 participants (27%) completed the test without missing a vehicle sound both times, which means they detected each at least once and their bar graphs did not include "yellow" colour. Conversely, the remaining subjects could not detect at least one of the vehicle sounds both times, which means their bar graphs included "yellow". More specifically, except for 4 participants, the rate of "yellow" (0 over 2) was below 25%. Among all the subjects, the lowest and highest detection rates were 43.75 and 93.75%, respectively.

Once the overall results are broken down by vehicle sound-based, depicted in Figure 4.10c, it is observed that detectability rates of cars are changing between 31.3 and 65.6%, these rates are significantly lower than trucks, which range from 51 to 100%. The detection rates of ICE truck at 10km/h and 20km/h are above 94.8 %, without any "yellow" colour, indicating that the ICE truck was never missed both times and almost always detected both times by participants.

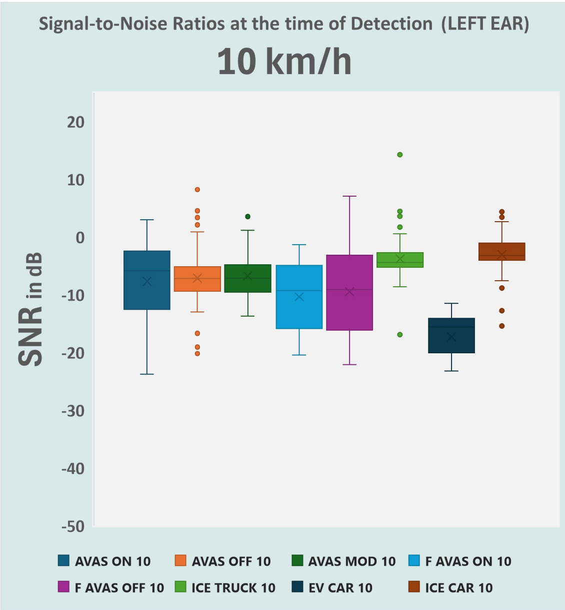
The presence of AVAS sounds (AVAS on mode) resulted in higher detection rates at both speeds, modulated AVAS sound did not create a significant difference at 10 km/h. However, surprisingly at 20 km/h, its detection rate was 100%. On the other hand, the lowest detection rates belonged to BEV truck’s sounds, in which tonal components were decreased by 12 dB(A), except for one (F AVAS ON 20). Their detection rates also show that filtered versions were more likely to be missed both times.

4.3.1.1 Signal-to-Noise Ratios at the time of detection

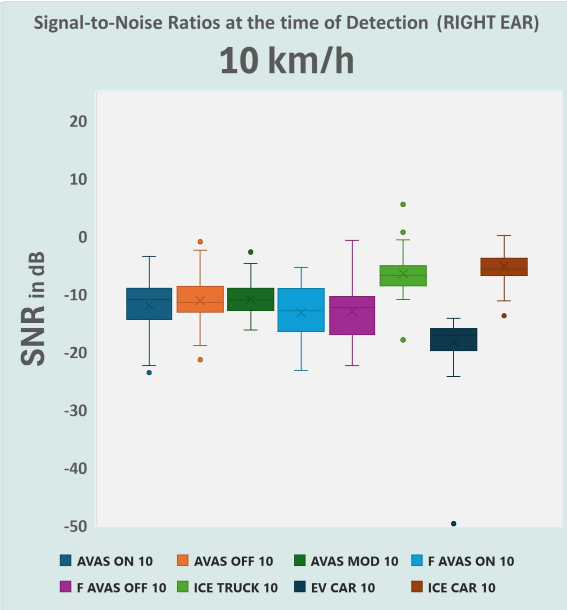
As detailed in the methodology chapter, five separate urban background noise files were used and randomly presented during the tests. The order of these background files was saved for each participant. Signal-to-noise ratios (SNR) were calculated using 1-second equivalent levels for background noise and 1-millisecond equivalent levels for vehicle sounds; each participant’s reaction times, which were tested before and after the listening tests, were taken into account for calculations[5].

[5] For instance, suppose that a vehicle stimulus started at the 16th seconds of the background noise and was detected 5.33 seconds later, 21.33th seconds of the background noise and the 5.33th seconds of the vehicle stimulus, the equivalent sound level between the 21st and 22nd seconds of the background noise was considered. Assume that the subject’s average reaction time was 330 ms, the equivalent level of 5th seconds of the vehicle stimulus was considered.

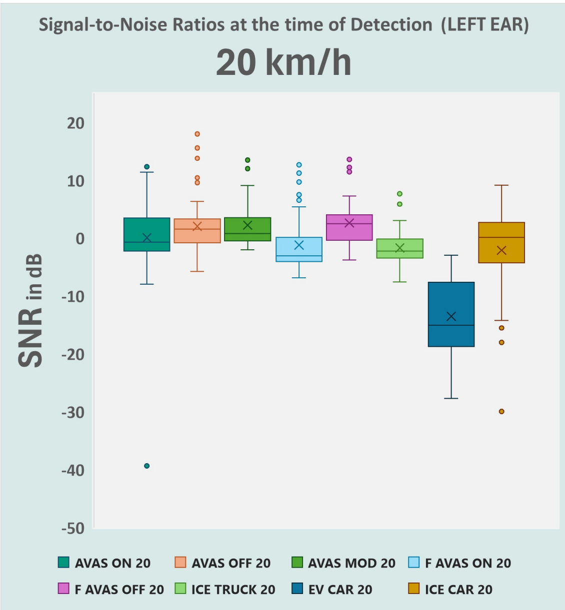
Figure 4.11 shows the SNRs at the time of detection for both vehicle speeds, both left and right ears.



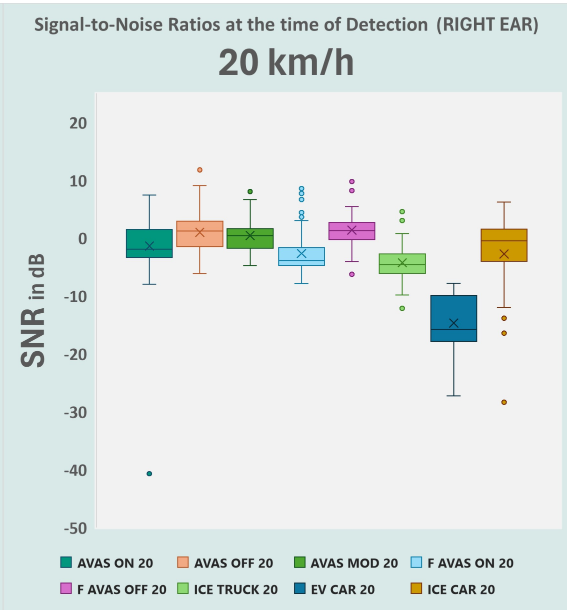
(a) Left Ear, 10 km/h



(b) Right Ear, 10 km/h



(c) Left Ear, 20 km/h



(d) Right Ear, 20 km/h

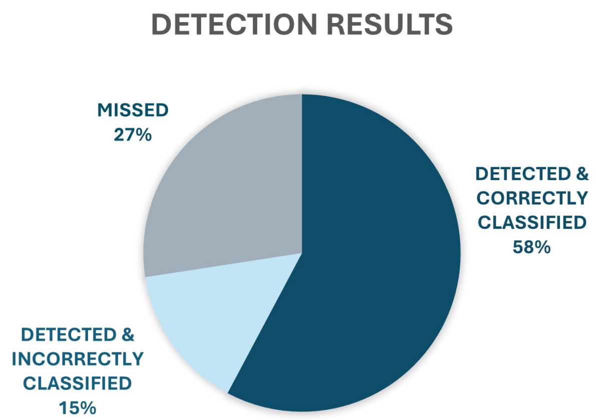
Figure 4.11: Signal to Noise Ratios for each Vehicle at the time of detection.

Considering the measurement setup, the left ear of the binaural head was closer to the roadside, which means it was closer to the sound source. Without any exception, all SNRs for the left ear were higher than the SNRs for the right ear; for 10 km/h, the differences between the ears ranged from 1 to 4.2 dB(A), while for 20 km/h, they ranged from 1.6 to 2.5 dB(A).

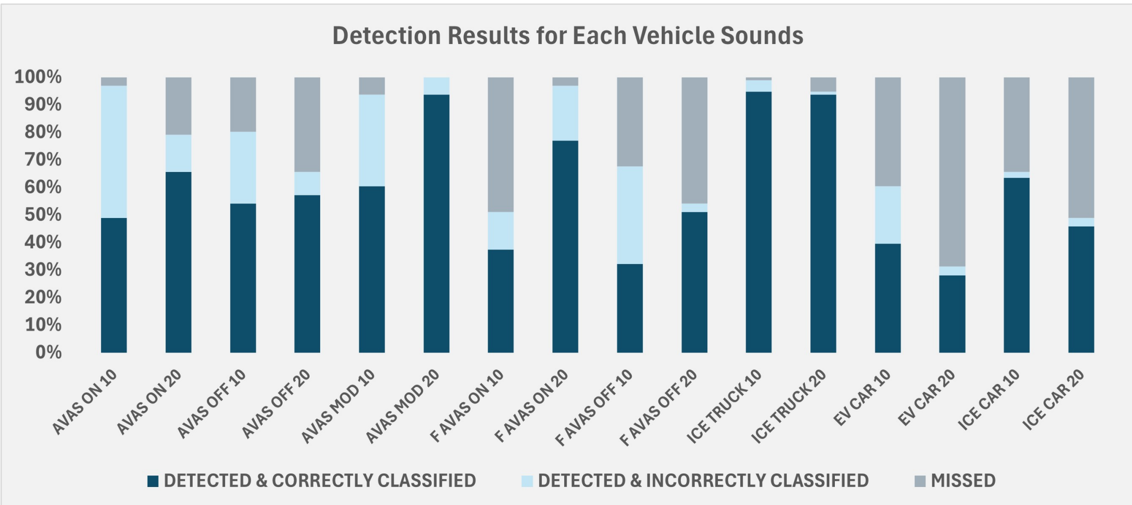
For 10 km/h and 20 km/h, mean values for SNRs (for the left ear) ranged between minus 3 to minus 10.3 dB(A) and minus 1.7 to plus 2.3 dB(A), respectively. EV car results were outliers at both speeds; the mean SNRs were minus 17.3 dB(A) for 10 km/h and minus 13.5 dB(A) for 20 km/h.

4.3.2 Case B: Can pedestrians accurately classify the detected vehicles?

This section focuses on whether the participants correctly classified the vehicles they detected. The overall detection results showed that 73% were detected and 27% missed. As seen in Figure 4.12a, 15% of the total results could not be correctly classified. In total, 58% of the vehicles could be correctly classified after being detected. Figure 4.12b details how these results are broken down on a per-vehicle basis.



(a) Overall Detection & Classification Results



(b) Detection & Classification Results for Each Vehicle Sound

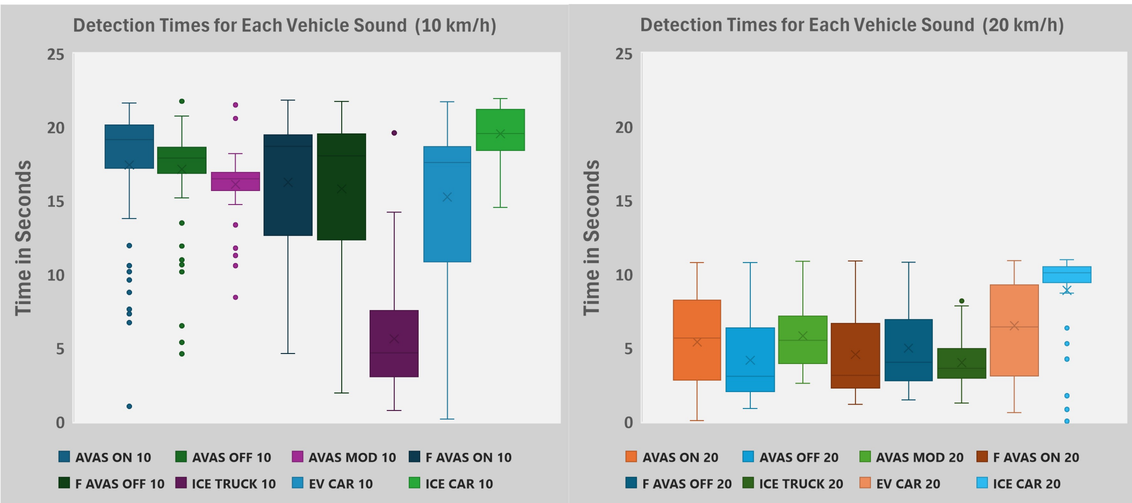
Figure 4.12: Detection Results when Classification Accuracy is Considered.

Among all vehicle types except ICE Car, the incorrect classification rate within detected ones was notably higher at 10 km/h, revealing higher accuracy rates in classification at 20 km/h. ICE Trucks were almost all correctly categorized at both speeds, with a slight improvement at 20 km/h. Among BEV trucks, the highest incorrect classification rate at 10 km/h when AVAS is in active mode, followed by BEV truck with reduced tonal components with AVAS in inactive mode. Similarly, EV Car had a high incorrect classification rate at 10 km/h, suggesting that while classifying participants were particularly hesitant between EV cars and BEV trucks at 10 km/h.

Although the use of AVAS sound provided higher detection rates compared to inactivated mode counterparts, incorrect classification rates were higher when AVAS was in active mode. This also may point out that the BEV Truck's AVAS sound and EV Car's AVAS sound could not be distinguished enough, within urban background noise.

4.3.3 Case C: Can pedestrians detect vehicles at safe distances?

In the previous sections, 4.3.1 and 4.3.2, results were analyzed without considering safe distances and included all detections within the 60-meter measurement segment. As a further step, this section examines whether participants detected vehicles at safe distances. Figure 4.13a and 4.13b show participants' detection times for 10 and 20 km/h vehicles, respectively. In these figures, zero refers to when the stimuli start and correspond to 50 m from the observer (binaural head), while 22 seconds (for 10 km/h) and 11 seconds (for 20 km/h) refer to when the stimuli end, approximately 10 m away from the observer after the vehicle passed, respectively.



(a) Vehicle Speed: 10 km/h **(b)** Vehicle Speed: 20 km/h

Figure 4.13: Detection Times for Each Vehicle Sound.

Using participants' detection times, depicted in Figure 4.13, corresponding distances[6] were calculated and illustrated in Figure 4.14. In this figure, the horizontal axis shows the distances in meters. The observer is positioned at the zero point on this axis, standing parallel to the road. Vehicles are approaching from 50 meters away behind the observer and continue for 10 meters after passing the observer. Each vehicle sound was represented in different colours, and the written numbers on each vehicle refer to mean detection distances and show the distance from the observer. The top of the figure shows the 10 km/h vehicle sounds, while the bottom depicts their 20 km/h counterparts. The red lines show the border of the unsafe zone[7], calculated as 11 m for 20 km/h vehicles and 5 m for 10 km/h vehicles.

As seen in Figure 4.14, most vehicles with a speed of 10 km/h were detected in the unsafe zone, except ICE Truck. Moreover, ICE Truck was the only vehicle where all detections were in the safe zone among all the vehicles regardless of vehicle speed. The mean detection distances of BEV truck with and without AVAS were in the unsafe zone and they had many outliers, suggesting that although some participants could detect in the safe zone, most of them found it hard. Similarly, although modulated AVAS and BEV truck with filtered tonal components performed better, their detection mean values were very close to the border of safe and unsafe zones, and modulated AVAS also had many outliers.

Unlike their 10 km/h counterparts, most vehicles with a speed of 20 km/h were detected in the safe zone, except for the ICE Car. Ice Truck outperformed at this speed again, but not all detections belonging to it were in the safe zone, like at 10 km/h. The mean detection distances of BEV truck with and without AVAS were in the safe zone, 19.9 and 25.8 m respectively; these average detection distances indicate that BEV Truck without AVAS was detected earlier on average than BEV Truck with AVAS. Filtering tonal components helped with the detection, the mean distance was higher than BEV truck with AVAS. Modulated AVAS detected slightly later compared to BEV truck with AVAS.

[6] To illustrate if it is supposed that a stimulus is detected at fifth seconds, this response for 10 km/h (2.78 m/s) corresponds to 13.9 m away from the starting point of the measurement and 36.1 m away from the observer, since the distance between the starting point and the observer is 50 m; and for 20 km/h (5.56 m/s) corresponds to 27.8 m away from the starting point and 22.2 m from the observer.

[7] The borders of the unsafe zone were decided through stopping distances of trucks with 10 km/h and 20 km/h constant speeds. Stopping distances were calculated based on these assumptions: road surface is asphalt and in dry conditions which gives $6\,\mathrm{m/s^2}$ acceleration (in a conservative scenario), reaction time for the driver is 1 second and reaction time for the system is 0.5 seconds (in the worst case).

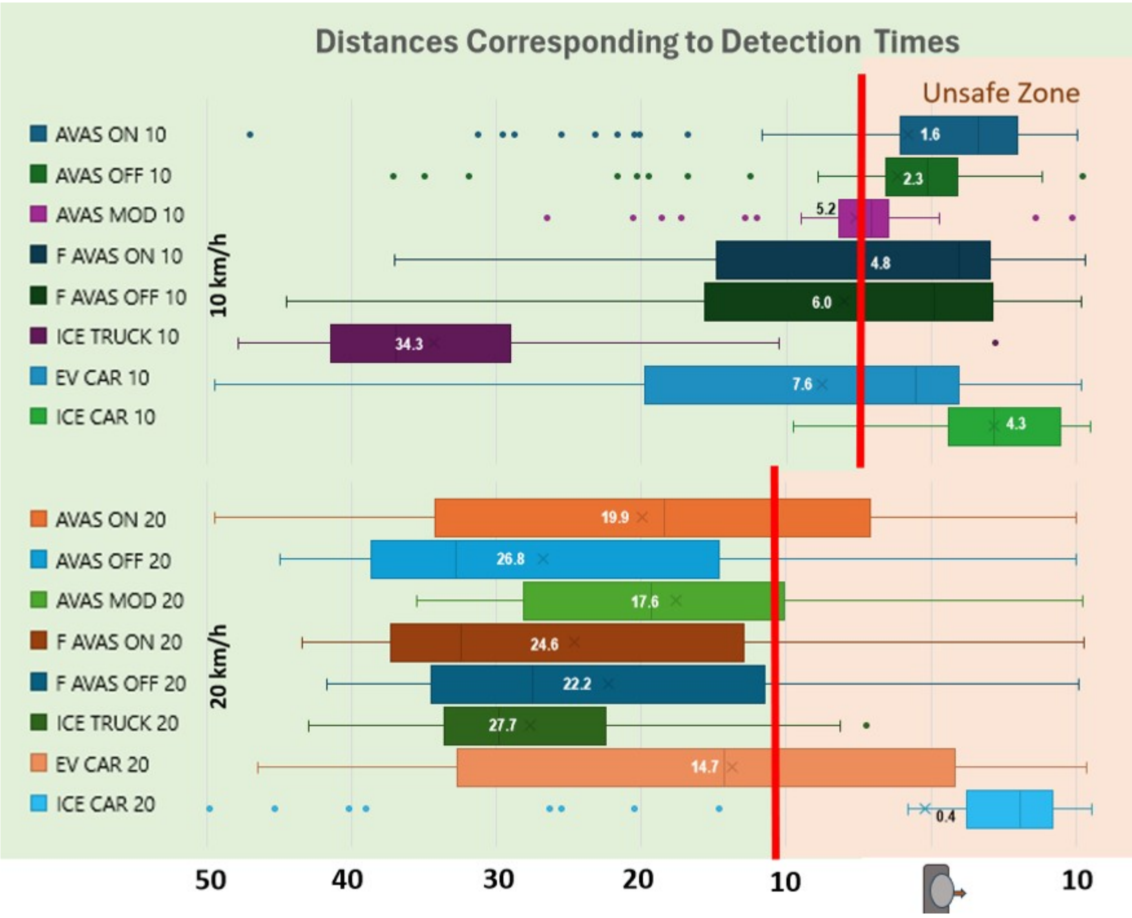
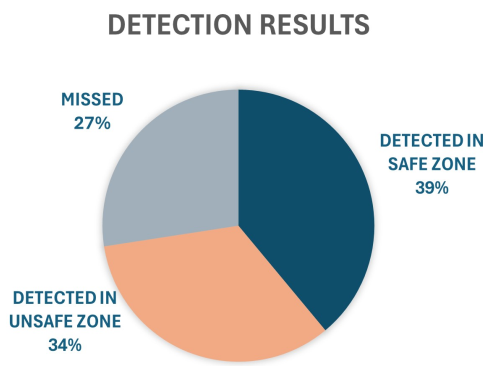


Figure 4.14: Distances Corresponding to Detection Times.

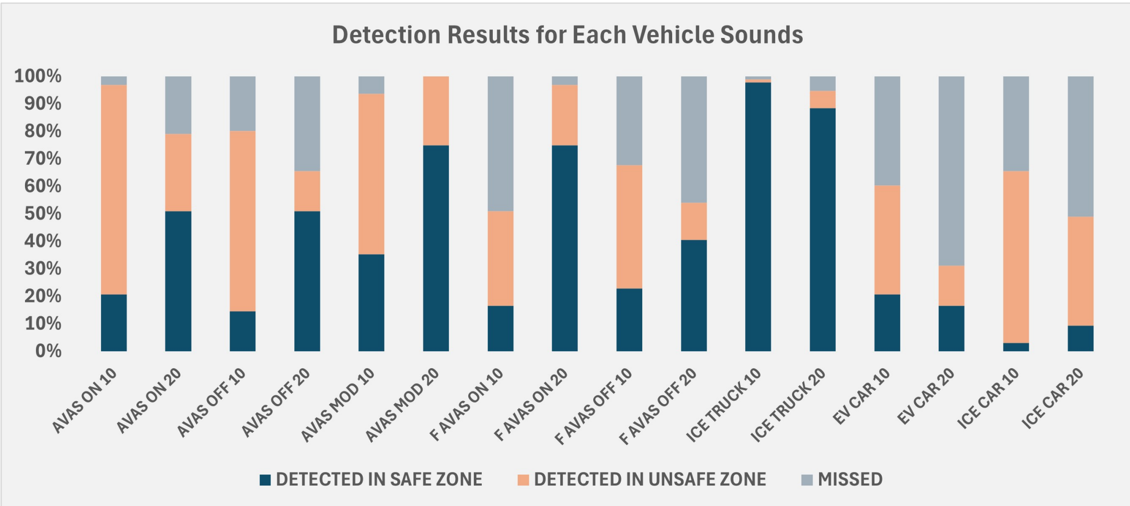
On the other hand, Figure 4.14 only presents the distances corresponding to detection times, naturally without concentrating on the undetected percentages. Overall results that considered missed percentages are illustrated in Figure 4.15a: 39% of the vehicles were detected in the safe zone, while 34% were in the unsafe zone.

Figure 4.15b details the detection results in safe and unsafe zones for each vehicle sound. At 10 km/h detection in safe zone rates of BEV Trucks ranged between 14.6% and 35.4%, BEV Truck with modulated AVAS had the highest rate; while at 20 km/h ranged between 51% and 75%, both BEV Truck with modulated AVAS and BEV Truck with filtered tonal components shared the highest rates.

Although the overall detection rate of BEV Truck with AVAS was higher than the BEV Truck without AVAS at both speeds, when focusing on detections only in the safe zone, BEV truck without AVAS was detected 5 percent lower than the AVAS-equipped truck at 10 km/h. At 20 km/h, the detection rates were the same. As a result, considering the safe distances, the presence of AVAS did not significantly change the detection rates. In addition, both BEV Truck with modulated AVAS and BEV Truck with reduced dominance of tonal components showed superior performance than BEV Truck with AVAS.



(a) Detection Results in Safe and Unsafe Zones



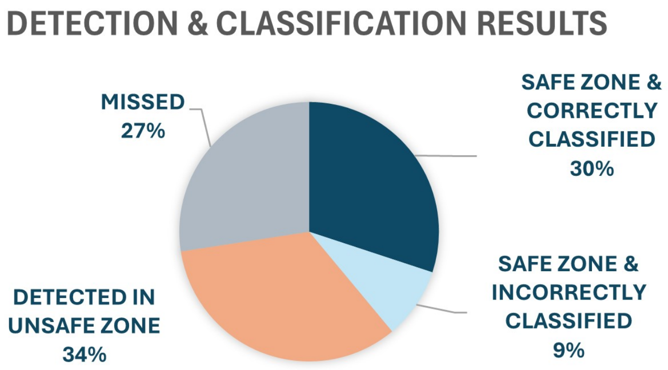
(b) Detection Results in Safe and Unsafe Zones for Each Vehicle Sound

Figure 4.15: Detection Results when Safe Distances Considered.

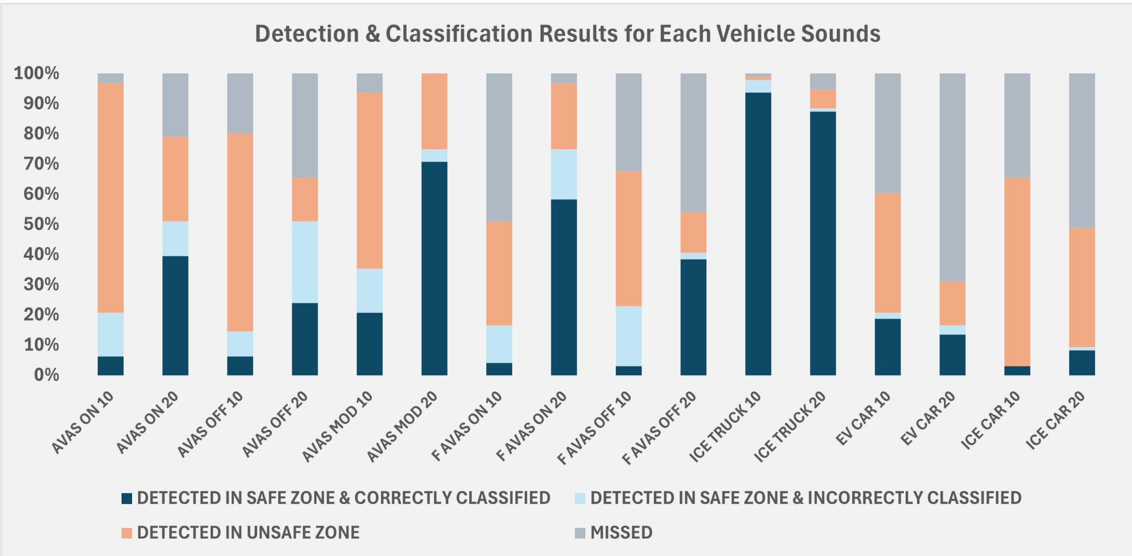
4.3.4 Case D: Can pedestrians accurately classify the vehicles that are detected at a safe distance?

As a final step, this section addresses whether the vehicles detected at safe distances were correctly classified. Figure 4.16a presents the overall results for this case, while Figure 4.16b shows the results for each vehicle.

As interpreted in the previous section, 39% of the vehicles were detected in the safe zone; 30% of the detected vehicles were correctly classified while 9% were incorrectly classified. ICE Truck, at both speeds, rarely incorrectly classified. At 10 km/h, the percentage of BEV trucks that were detected at safe distances and then correctly classified varied between 3.1 and 6%, except for the BEV Truck with modulated AVAS (20.8%).



(a) Detection & Classification Results in Safe and Unsafe Zones



(b) Detection & Classification Results in Safe and Unsafe Zones for Each Vehicle Sounds

Figure 4.16: Detection Results when Safe Distances and Classification Accuracy Considered.

At 20 km/h, detected and then correctly classified BEV Trucks' rates changed between 24% and 70.8%, the presence of AVAS helped with correctly classifying the detected vehicle. In addition, the trend did not change; both BEV Truck with modulated AVAS and BEV Truck with reduced dominance of tonal components showed superior performance than BEV Truck with AVAS. Especially, the incorrect classification rate of detected BEV Truck with modulated AVAS was quite lower compared to BEV Truck with AVAS.

4.3.5 Summary of Detection Part Outcomes

During the detection & classification part of the test, within continuous urban background noises for 1-minute duration each, participants were tasked to detect approaching vehicles and then to classify the detected vehicle whether the sound they heard belonged to a car or a truck as soon as possible. 15 clips were presented in total. Each 1-minute clip consisted of up to 3 vehicle passages. Participants' detection times, classification responses and the order of their background samples were saved.

Analysis of the results addressed four sub-questions (cases). The first case only focused on detection results without considering the safe distances, SNRs also were presented at the time of detection. The second case focused on whether the detected vehicles, shown in the first case, were correctly classified. The third case examined whether participants detected vehicles at safe distances and the last case addressed their classification accuracy.

Align with the classification part results of the test, ICE Truck consistently outperformed at both speeds, participants detected and then classified them more easily. The BEV truck with modulated AVAS and filtered tonal components outperformed its unmodulated and unfiltered versions, suggesting that these modifications provided participants with more clues for both detection and classification. Furthermore, when considering safe distances, the detection rates of BEV Trucks changed significantly according to vehicle speed. At 10 km/h, the detection rates in the safe zone were low, and the average detection distances were very close to the unsafe zone or the border between safe and unsafe zones. At 20 km/h, the detection rates in the safe zone were higher, and all average detection distances were in the safe zone. On the other hand, the overall results showed that 39% of the total were detected in the safe zone, with a high contribution from ICE Trucks in this percentage. When the classification accuracy was also taken into account, the total percentage decreased to 30%, maintaining the high contribution of ICE trucks.

These findings revealed that participants had difficulty detecting BEV trucks, especially at 10 km/h, at safe distances within urban background noise. The presence of AVAS did not help to achieve higher detection rates. However, the presence of AVAS modulation and filtering effects (tonal components of the BEV truck) played a significant role in both detection rates and classification accuracy.

4.4 The Role of AVAS in Future Urban Environments

Considering that the percentage of electric and hybrid vehicles in urban environments will increase, how the functionality of Acoustic Vehicle Alert Systems (AVAS) will be shaped in the future matters. In this regard, this section aims to discuss the impacts of AVAS not only from the viewpoint of replacing only the vehicle fleets but also to explore the role of AVAS in future urban environments from key aspects.

4.4.1 Future Directions for AVAS Technology

AVAS's future directions can be discussed from several key perspectives: safety, product development, urban sound planning, and urban mobility.

4.4.1.1 From Safety Perspective

From a safety standpoint, the fundamental functionality of AVAS is effectively warning vulnerable road users. While doing this, the system should not create any additional environmental noise. On the other hand, this primary function is still far from fulfilled due to the complex nature of urban environments. AVAS can be ineffective in one urban ambient may be adequate in another (Yamauchi et al., 2015), or may emit unnecessary noise to the environment and consequently be unfunctional. Therefore, rather than focusing on stable and constant sounds, responsive and adaptive AVAS with spontaneous urban ambient would promise more positive results for safe urban environments (Berge and Haukland, 2019; Fontecha et al., 2022; Kournoutos, 2020; Yamauchi et al., 2015)

On the other hand, counterarguments were expressed on the necessity of AVAS and its safety function. According to Sandberg et al., 2010 quiet vehicles are not a new problem and there is no clear evidence[8] that they are problematic in a safety manner. Their recommendation was mainly highlighting combat the environmental noise levels to make quiet vehicles audible, instead of adding warning signals to vehicles. Moreover, if it is proven that electric vehicles pose a risk for vulnerable road users, they suggested that the defined problem can be solved by using non-acoustical solutions. In his following review Sandberg suggested to stop focusing on AVAS sound and pointing out that from a safety manner, there would be a responsibility shift from drivers to pedestrians. In a conventional approach, drivers have the main responsibility, since as their names suggest vulnerable road users are unprotected. Thus, by using warning signals, drivers may be less careful since they are "warning" them (Sandberg, 2012).

[8]Hoogeveen, 2011 studied accidental risks of electric vehicles and findings revealed that there was no solid proof of more accidents involving electric vehicles and vulnerable road users. At this point, it is worth highlighting that Sandberg's and Hoogeveen's studies published in 2010 and 2011. A current study, based on 2013-2017 data in the UK, showed that pedestrians are twice as likely to be hit by an electric or hybrid-electric car than an internal combustion engine car (see Edwards et al., 2024)

4.4.1.2 From Product Development Perspective

Although all hybrid and electric vehicles are mandated to be equipped with AVAS, no standardized AVAS sound is defined through legislation. This allows brands to design their signature AVAS sound. According to Parizet et al., 2016 it is a chance for car manufacturers since manufacturers can fully design the exterior sounds of their products. For this reason, manufacturers should consider future needs, in the short and medium term the vehicle fleet will continue to be dominated by combustion vehicles but with an increasing share of electric vehicles, the required sound features of AVAS will change, and rather than sound levels quality of AVAS sound will become forefront.

Moreover, to be able to make AVAS functional in urban areas, synergies between different brands are important to avoid possible future cacophony. Due to the fact that manufacturers focus on individually designing their vehicle alert sounds, in reality, vehicle sounds may be superpositioned, which may consequent annoying and ineffective sounds rather than ensuring safety (Fiebig, 2020; Genuit, 2013).

4.4.1.3 From Urban Sound Planning Perspective

The ongoing energy transition is a chance to reshape our planning practices to create more sustainable urban environments. Shifting from combustion vehicles to their electric counterparts may be advantageous from an urban sound planning perspective if required actions are taken. Common initial thoughts on electric vehicles' "always" silence have been refuted by previous studies.(see e.g. Campello-Vicente et al., 2017; Genuit, 2013; Verheijen and Jabben, 2010).

Previous findings revealed that the advantages of silence of electric vehicles heavily depend on vehicle operating speeds, and electric vehicles are silent at low speeds. To illustrate according to Verheijen and Jabben, 2010 research, shifting to 100% electric car fleet provided a 3 to 4 dB decrease in existing urban traffic noise in selected areas for research in Utrecht, Netherlands and reductions were negligible above 50 km/h speeds due to dominance of tyre noise. Similarly, Campello-Vicente et al., 2017 investigated how electric vehicles will affect urban noise maps. Their findings align with the abovementioned study, above 50 km/h the effect could be ignored. However, at 30 km/h if the whole vehicle fleet consists of only electric ones, a 2 dB sound level reduction would be possible. In case their AVAS is activated, a 1 dB reduction is estimated instead of 2 dB. Bühlmann and Egger, 2017 investigated possible advantages of using a speed limit of 30 km/h in defined zones in urban areas. Their findings showed that up to 5dB reduction can be achieved, but they highlighted heavy vehicles were not considered in the study.

Furthermore, to turn this vehicle fleet transition into an advantage from an urban sound planning perspective, a more holistic approach is needed beyond just focusing on the replacement of the vehicle fleet. For instance, both Cesbron et al., 2021 and Pallas et al., 2020 explored whether electric vehicle noise emission affected by road surfaces. Their findings suggested low noise tyres and quiet road surfaces can further contribute to noise reduction. Cesbron's findings revealed that up to 6.2 dB(A) reduction can be achieved due to road surface variance.

Last but not least, urban quiet areas need to be handled carefully. Using constant AVAS sounds may create potential risks for urban quiet zones. Their "quietness" could become damageable by uncareful planning (Kihlman et al., 2014; Laib and Schmidt, 2019). More exploration would be beneficial in investigating adaptive AVAS and taking advantage of AVAS's responsiveness to the current urban ambience (Fontecha et al., 2022).

4.4.1.4 From Urban Mobility Perspective

To estimate the role of AVAS in the future environment, there is also a need to consider how societies' mobility habits will change and how these trends will affect future urban soundscapes. Can et al., 2020 handled possible changes in urban mobility habits in future and their links to the future urban sound environments. Their analysis points out more flexible life routines which means that conventional peak hours of urban traffic or citizens' daily transportation habits may change, consequently, noise levels may vary. Although estimations point out decreasing car ownership in future cities, the need for urban logistics is foreseen to increase, and night delivery is forefront among the targeted solutions, which means heavy vehicles' noise emissions will be more crucial to be considered in future environments.

5
Conclusion

The primary objective of this study was to investigate the detectability of battery electric trucks[1] (BEV trucks) equipped with Acoustic Vehicle Alert System (AVAS) compared to internal combustion engine (ICE) trucks in urban areas, where background noise may mask AVAS sounds. In addition, the functionality of AVAS was investigated by comparing BEV truck without AVAS, BEV truck with modulated AVAS, and BEV truck with reduced dominance of tonal components: the effect of these modifications on detectability and classification accuracy was analyzed. The study also examined whether BEV trucks were distinguishable from cars in quiet outdoor environments with low background noise levels (the equivalent levels were around 45 dB(A)) and continuous urban background noise with higher levels (the equivalent levels were ranging between 57 and 62 dB(A)).

5.1 Inferences from the Present Study

Before highlighting the findings, it is worth recalling the limitations of the study, detailed in the introduction chapter, that may impact the generalizability of the findings: a single brand-specific AVAS sound was tested, a limited number of vehicles were included in the study, background noise was recorded in a single city (Stockholm), the tests did not cover all real-world dynamic driving conditions, only steady speeds (10 and 20 km/h). Distinct weather conditions were not considered, only dry asphalt conditions without precipitation were tested. Measurements of a single binaural head position were used in the listening tests. Finally, the tests were conducted in a controlled listening environment via headphones.

Within the mentioned limitations, key findings can be summarised as follows: ICE trucks consistently outperformed BEV trucks. Participants easily distinguished ICE trucks from cars within quieter outdoor environments, and almost all participants detected and accurately classified ICE trucks in the safe zone[2] within higher, con-

[1]Heavy trucks in Category N3, which are used for the carriage of goods and have a mass exceeding 12 tonnes, were utilized. For the vehicles used in the study, please see Table 3.1.

[2]The borders of the unsafe zone were decided through stopping distances of trucks with 10 km/h and 20 km/h constant speeds. Stopping distances were calculated based on these assumptions: the road surface is asphalt and in dry conditions, which gives an acceleration of $6\,\mathrm{m/s^2}$ (in a conservative scenario); the reaction time for the driver is 1 second; and the reaction time for the system is 0.5 seconds (in the worst case). These calculations resulted in 11 m for 20 km/h vehicles and 5 m for 10 km/h vehicles. Therefore, if a vehicle was closer than 11 m at 20 km/h or 5 m at 10 km/h to the observer, it was considered unsafe (see Figures 4.8 and 4.14).

tinuous urban background noises(the equivalent levels were ranging between 57 and 62 dB(A)). BEV trucks' classification accuracy and detection rates provided inconsistent results that were highly affected by vehicle speeds: Participants more easily classified BEV trucks in the safe zone when they passed at 10 km/h within quieter outdoor environments(the equivalent levels were around 45 dB(A)). Unlike this, participants struggled to detect them at 10 km/h in the safe zone within higher, continuous urban background noises. Although BEV trucks' performance improved at 20 km/h, overall results revealed that only 30% of vehicles were detected and correctly classified within safe zones, with ICE trucks' significantly high contributions to this rate. BEV truck with modulated AVAS and filtered tonal components outperformed its unmodulated and unfiltered counterparts, suggesting that these modifications aided participants in both detection and classification.

Although the current regulation allows brands to create their own signature sounds, these results demonstrate that a sound design that complies with the regulation may be inconsistent while warning pedestrians in urban areas due to the masking effect. On the other hand, if this study's results had displayed that the tested AVAS sound could be detected in the safe zone, they would still be far from generalizable and stay on a case-by-case basis, further investigations are needed. In this context, designing an AVAS sound which is functional at all times and under all conditions without creating extensive environmental noise is a challenge and needs further investigation. In ideal conditions, an AVAS sound would adapt to its current ambient and revise its frequency content and sound levels (following the regulations), thus warning vulnerable road users without creating extensive environmental noise. In addition, the functionality of AVAS sound may vary depending on which vehicle it is equipped with. For example, only one BEV truck was tested in this study, but once the dominance of the tonal components of the vehicle used was changed, their detectability rates changed, which means the same AVAS sound led to different results in different vehicles.

5.2 Suggestions for Further Research

The present study's findings may provide insights into current and future needs in designing AVAS sounds for electric trucks. By handling the limitations of this study, future investigations can build on the current findings and contribute to the development of more effective, adaptive AVAS sounds, ensuring safer urban areas for vulnerable road users in both current and future increasingly electrified urban environments.

Future research could be more comprehensive by aiming to handle several critical scopes to enhance the generalizability and applicability of their findings by considering including a large number of AVAS sounds, a wider variety of vehicle types and models that reflect urban traffic circumstances, urban background noises from multiple cities with variable soundscapes, various weather conditions, and dynamic driving conditions by including acceleration and deceleration, increasing the use of binaural head positions to mimic human auditory perception better.

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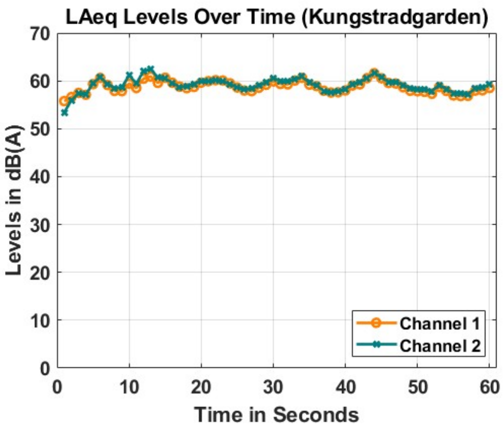
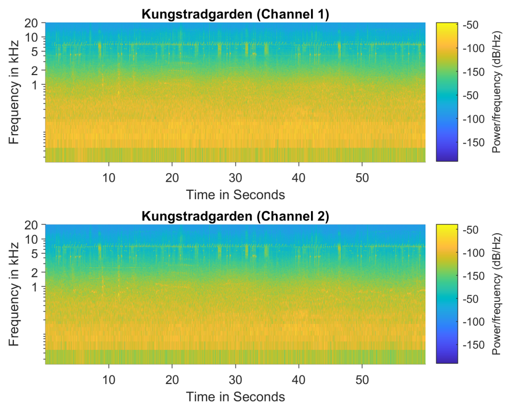
A

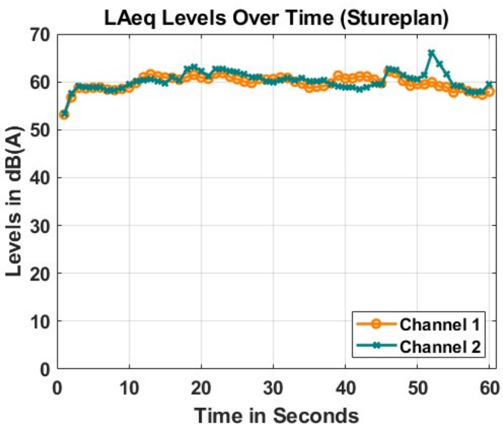
Appendix 1



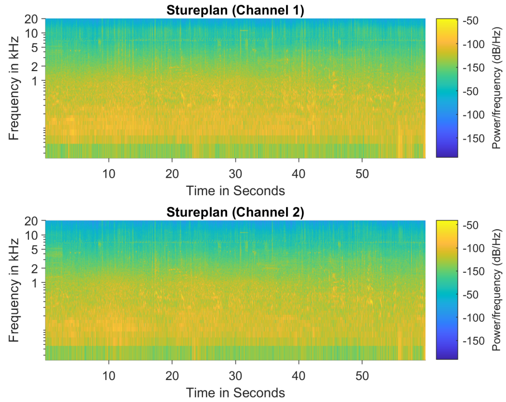
(a) Kungsträdgården, Levels



(b) Kungsträdgården, Spectrograms

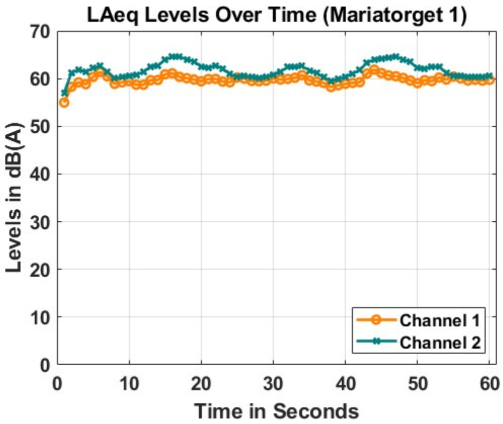


(c) Stureplan, Levels

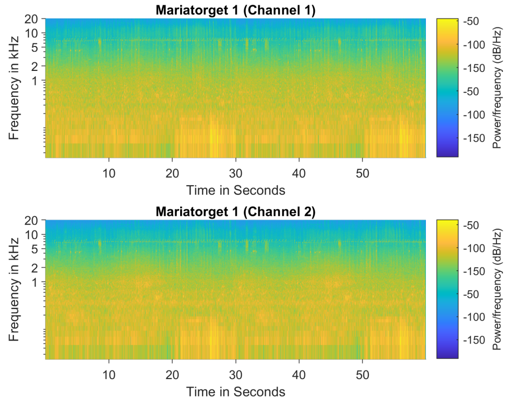


(d) Stureplan, Spectrograms

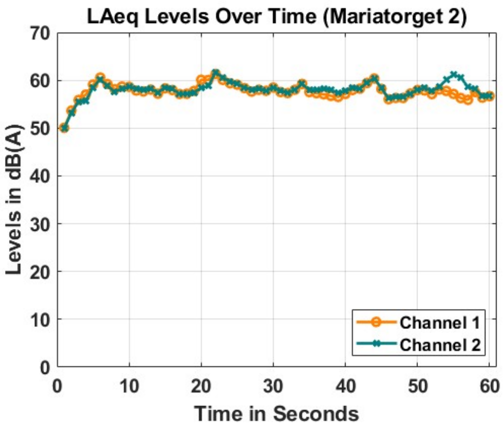
Figure A.1: A-Weighted Equivalent Levels and Spectrograms of Urban Background Files Used in the Listening Tests.



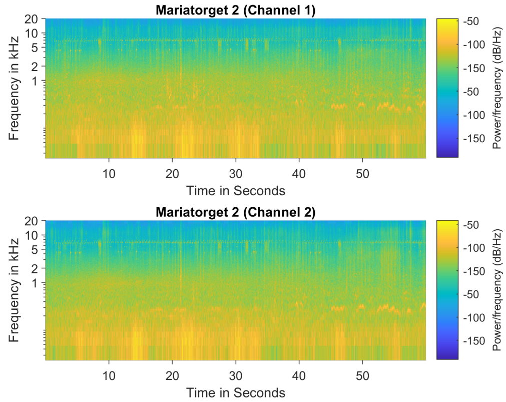
(a) Mariatorget 1, Levels



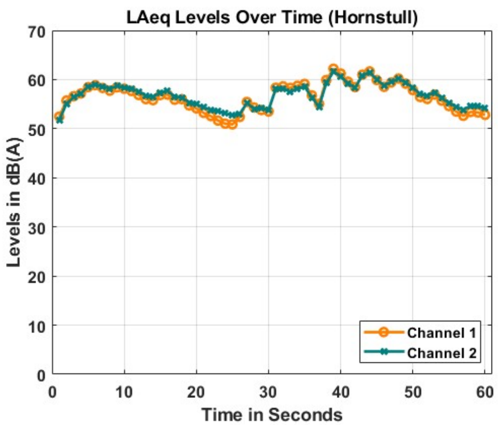
(b) Mariatorget 1, Spectrograms



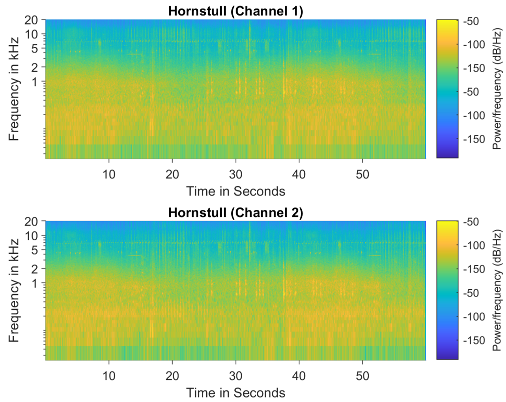
(c) Mariatorget 2, Levels



(d) Mariatorget 2, Spectrograms

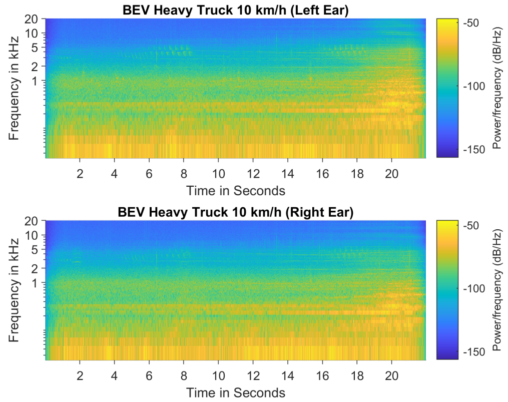


(e) Hornstull, Levels

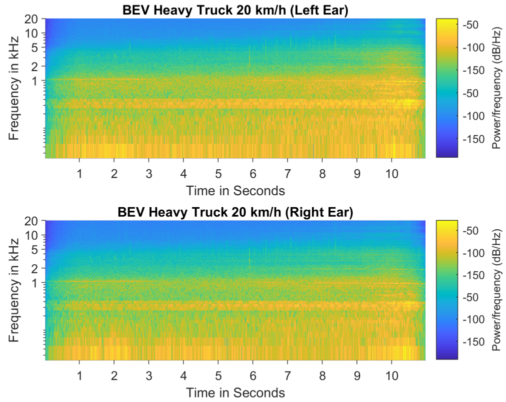


(f) Hornstull, Spectrograms

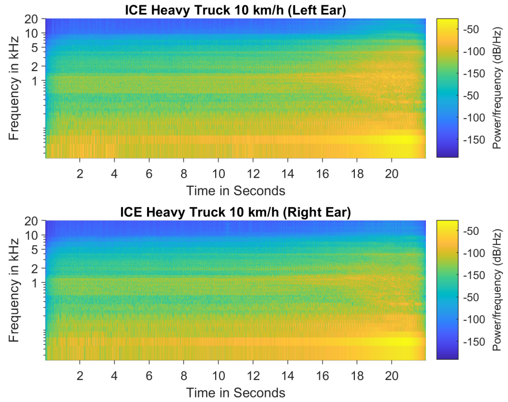
Figure A.2: cont. A-Weighted Equivalent Levels and Spectrograms of Urban Background Files Used in the Listening Tests.



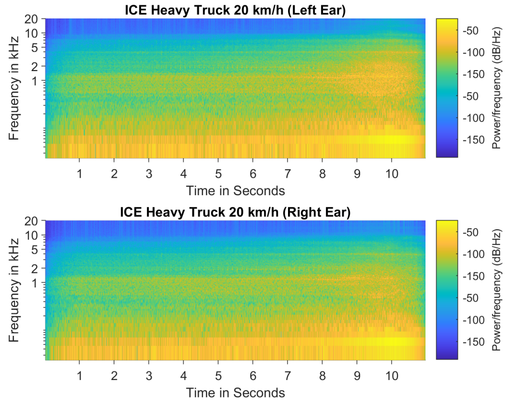
(a) BEV Heavy Truck AVAS on, 10 km/h



(b) BEV Heavy Truck AVAS on, 20 km/h

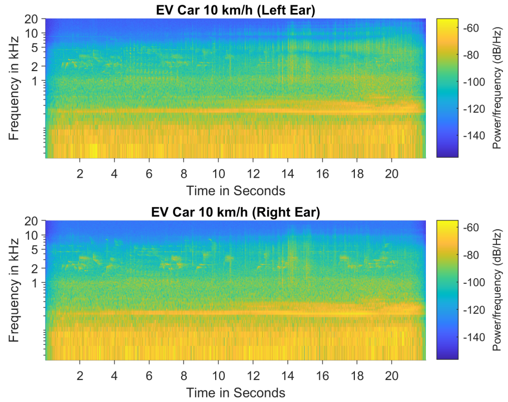


(c) ICE Heavy Truck, 10 km/h

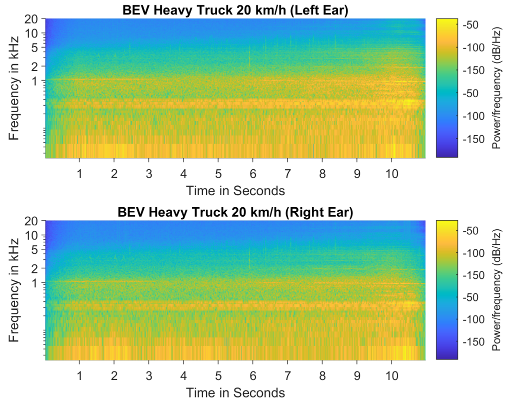


(d) ICE Heavy Truck, 20 km/h

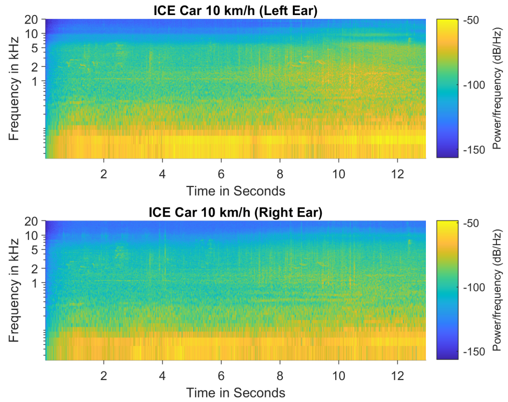
Figure A.3: Spectrograms of Vehicle Sound Files Used in the Listening Tests.



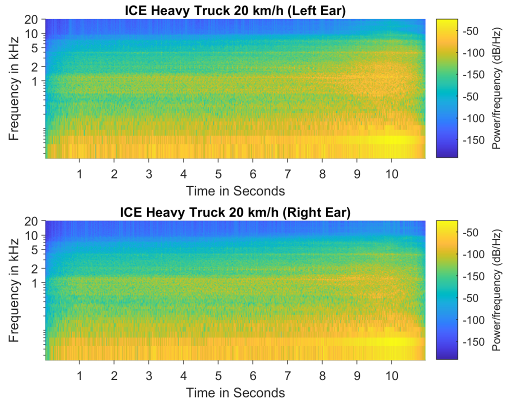
(a) BEV Passenger Car AVAS on, 10 km/h



(b) BEV Passenger Car AVAS on, 20 km/h



(c) ICE Passenger Car, 10 km/h



(d) ICE Passenger Car, 20 km/h

Figure A.4: Spectrograms of Vehicle Sound Files Used in the Listening Tests.

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