THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Guidelines for methods studying human perception of sound and vibration in passenger cars

Xiaojuan Wang

Department of Industrial and Materials Science

Division Design and Human Factors

CHALMERS UNIVERSITY OF TECHNOLOGY

Gothenburg, Sweden 2024

Guidelines for methods studying human perception of sound and vibration in passenger cars

Xiaojuan Wang

© Xiaojuan Wang, 2024. ISBN: 978-91-8103-145-4

Löpnummer: 5603

ISSN 0346-718X

Published and distributed by

Department of Industrial and Materials Science
Division Design and Human Factors
Chalmers University of Technology
SE-412 96, GOTHENBURG, Sweden
Telephone + 46 (0) 31-772 1000

Printed by Chalmers Reproservice

Gothenburg, Sweden 2024

Abstract

As automotive technology advances, particularly in combustion-engine (CV) and electric vehicles (EV), ride comfort has become a critical attribute for future car development. A multitude of factors, including seat, sound, and vibration, significantly influence the perceived ride comfort in passenger cars. Despite numerous studies on human responses to sound and vibration, there is a noticeable gap in research investigating real occupants' experiences under various real-world driving scenarios. Additionally, there is a lack of clear guidelines for utilizing advanced technologies in the study of ride comfort.

This thesis aims to bridge this gap by examining human experiences of sound and vibration in conventional passenger cars, developing methodologies to assess their impact on perceived ride comfort. The primary purposes of this thesis are as follows: (1) to define ride comfort from the occupant's perspective, identifying factors that influence it, (2) to investigate how sound and vibration specifically affect ride comfort, and (3) to propose guidelines and a framework for using advanced technologies in studying ride comfort.

The research methodology encompasses a literature review, a field study on sound and vibration experienced during various driving scenarios, an interview study on the use of driving simulators, the development of a machine learning framework, and a focus group study to evaluate the proposed framework.

The literature review reveals that while significant findings are available from laboratory settings, studies integrating all parameters affecting overall ride comfort in real-world contexts are limited. Furthermore, there is a need to delve deeper into how sound and vibration influence occupants' overall ride comfort.

To address this, the field study was conducted using eight typical driving scenarios with ten participants in both a CV and an EV. Results indicated similarities in initial comfort aspects such as seat adjustment and body room but differences in dynamic discomfort, with body movements being a concern in the CV, and sound annoyance more prominent in the EV. Moreover, induced body movements dominated vibration discomfort, while sound annoyance consistently compounded over time, making relaxation difficult for occupants.

In addition to field studies, this thesis also explores the role of driving simulators in user performance, experience, and ride comfort studies. Through an interview study involving 14 participants, guidelines for using high-level driving simulators were proposed. The research acknowledges the advantages of simulators, such as improved safety, repeatability, controllability. Furthermore, it emphasizes their capability to isolate variables and conduct experiments with fewer physical constraints, along with enabling rapid transitions between components, structures, and vehicle models. However, the research also addresses limitations, including space constraints and communication difficulties.

To tackle the challenges of traditional ride comfort evaluations, this thesis proposes a machine learning framework to overcome limitations such as data quality and quantity, cross-study comparison, and model interpretability. This framework aims to augment existing data, propose suitable performance metrics, and improve the accuracy and reliability of ride comfort prediction models. Additionally, a focus group study evaluates the feasibility of these machine learning methods, identifying their advantages of enhancing prediction performance and refinement methods that could be integrated.

In conclusion, this thesis provides a set of guidelines derived from field studies, driving simulator research, and innovative machine learning approaches to address the multifaceted nature of ride comfort in automotive design.

Acknowledgements

This research presented in this thesis has been funded by Zeekr Technology Europe AB, Gothenburg, Sweden, which has supported my industrial PhD studies.

I would like to express my deepest gratitude to my main supervisor, Prof. AnnaLisa Osvalder at the division of Design and Human Factors, for your unwavering support and guidance, which led me to this research topic. Your scientific rigor and curiosity have been a constant source of inspiration in my research. Thank you for your meticulous attention to detail and valuable feedback, which have helped me grow both professionally and personally.

I am also deeply thankful to my co-supervisor, Associate Prof. Patrik Höstmad from the division of Applied Acoustics, for your consistent support, constructive feedback, and encouragement. Your invaluable insights and assistance in writing papers have greatly enriched my work. I have learned much from you, especially in analyzing research problems and presenting results.

I would also like to extend my gratitude to Ingemar Johansson and Erik Preihs, my former manager and project leader, for your kind guidance and career advice throughout my research project. My sincere thanks also go to my previous manager Lars Nilsson, my current manager Mark Saukkonen, and my project leader, John Bergström, for your incredible support. Additionally, I am grateful to Shafiq Urréhman, Jörgen Sjöström, and Pradeep Singh Chauhan for their advice and support.

I would also like to thank Oscar Rexfelt and Lars-Ola Bligård at the Research School Human-Technology-Design for creating interesting PhD courses, and stimulating meetings and workshops among PhD students and supervisors. Also, thanks to Professor Marianne Karlsson from Design and Human Factors for interesting discussions. A special thanks to Johan Isaksson-Dawn for valuable help concerning machine learning, and to Melina Makris for insightful discussions about comfort issues in cars. I also wish to thank all participants in the empirical study for their invaluable contributions. I moreover want to express my appreciation to the Division of Applied Acoustics at Chalmers for support.

Furthermore, I extend my gratitude to my many colleagues both at Chalmers and Zeekr for selflessly sharing their knowledge and advice. To my friends both in Sweden and afar, thank you for your encouragement and companionship.

Lastly, I would like to thank my husband, Li, who is also my best friend: your support means more to me than words can express. My deepest thanks go to my son Lucas and my parents for their unwavering love and understanding.

Appended publications

Xiaojuan Wang has taken on the role of executing database searches, reviewing literature, planning and conducting studies, analyzing data, and writing and editing manuscripts. In paper A, Wang executed the database search, reviewed the literature, and wrote the paper with feedback from other authors. For papers B, C, D, and E, Wang further demonstrated an involvement by planning and conducting the studies, analyzing data, and composing and refining the manuscripts with input from co-authors.

Paper A

X. Wang, A-L. Osvalder, P. Höstmad, and I. Johansson (2020). “Human Response to Vibrations and Its Contribution to the Overall Ride Comfort in Automotive Vehicles: A Literature Review”, SAE Technical Paper, 2020.

Paper B

X. Wang, A-L. Osvalder and P. Höstmad (2022). “Sound and Vibration Influence on Overall Ride Comfort in a Conventional Passenger car under Different Driving Scenarios”. International Journal of Human Factors and Ergonomics, 2023.

Paper C

X. Wang, P. Höstmad and A-L. Osvalder (2022). “Influence of Sound and Vibration on Perceived Overall Ride Comfort: Comparison between an Electrical Vehicle and a Combustion Engine Vehicle”. SAE International Journal of Vehicle Dynamics, Stability, and NVH, 2023.

Paper D

X. Wang, P. Höstmad and A-L. Osvalder (2024). “Guidelines for using high-level driving simulators in user studies –assessing user performance, experience, and ride comfort”. To be submitted to International Journal of Vehicles.

Paper E

X. Wang, P. Höstmad, A-L. Osvalder and S. Urréhman (2024). “An approach to predicting riding comfort via machine learning: Integrating objective measurements of sound and vibration with occupant individual characteristics”. To be submitted to International Journal of Vehicle Noise and Vibration.

Table of Contents

Chapter 1: Introduction

1.1 Background

With the continuous advancements in vehicle refinement, ride comfort has become a significant focus in the development of new vehicles and platforms. Modern consumers now have elevated expectations for ride comfort in contemporary cars (Harrison, 2004; Sheng, 2012). A comfortable riding experience is essential for improving driver performance, reducing occupant fatigue, and enhancing safety and long-term health (Wang et al., 2020b). Consequently, both industry engineers and academic researchers are increasingly engaging in studies focused on ride comfort.

Human perception of ride comfort is influenced by ambient, dynamic, and ergonomic elements. Ambient factors include air temperature, air quality, and sound, while dynamic factors encompass vibration, impact, ride motion, and acceleration. Ergonomic factors cover visibility, functionality, seat architecture, seatbelts, and seat-human interfaces (Wang et al., 2020b). These factors interact with one another; for instance, higher-magnitude vibrations can mask discomfort caused by lower noise levels and vice versa (Huang, 2012).

Research on ride comfort for seated occupants has predominantly focused on discomfort. Helander and Zhang (1997) established that comfort and discomfort can function as independent factors. Comfort is associated with well-being and relaxation and remains relatively constant over time, whereas discomfort is primarily linked to physical constraints and poor biomechanics. Other studies have also highlighted that experienced vibrations and ride motion (Wang et al., 2020b), as well as perceived sound levels and sound characteristics (Sheng, 2012), correlate with discomfort. Helander and Zhang (1997) further observed that experiences of discomfort are cumulative over time, leading to varying perceptions of discomfort between shorter and longer rides. Kamra et al. (2017) differentiated static comfort/discomfort, pertaining to perceptions in a stationary vehicle, from dynamic comfort/discomfort, related to perceptions in a moving vehicle.

A variety of studies have investigated human responses to vibrations and the vibrations in real vehicles. Wang et al. (2020b) summarized that vibration experiences in passenger cars can degrade overall ride comfort, induce motion sickness, and interfere with activities during the ride. The review of laboratory studies indicated that seated humans are most sensitive to vertical vibrations in the range of 4–6 Hz and horizontal vibrations in the range of 1–4 Hz. Weighted vibrations in passenger car seats were typically significant below 20 Hz in the lateral and vertical directions and below 30 Hz in the fore-and-aft direction.

Human responses to sounds and the sounds in real vehicles have been another focus of study. Studies on human responses to sound have revealed that both the frequency and amplitude of noise significantly impact perceived annoyance and discomfort (Sheng, 2012). Low-frequency noise below 250 Hz is particularly bothersome, leading to increased annoyance and reduced task performance (Waye and Rylander 2001a), while high-frequency sounds can cause irritation and concentration difficulties (Pawlaczyk-Luszczynska and Dudarewicz, 2020). Higher sound pressure levels correlate with greater annoyance (Nilsson, 2007), and fluctuating noises are more disturbing than constant ones (Plack, 2018). Tonal noises are moreover perceived as louder and more annoying than broadband noise (Fastl and Zwicker, 2007). Individual differences, including noise sensitivity, also play a crucial role in how sound is perceived, with more sensitive individuals experiencing greater annoyance at lower levels (Zwicher, 1977).

Clark et al. (2006) indicated that cabin sound can lead to annoyance and discomfort. Qatu et al. (2009) showed that in combustion-engine vehicles (CVs), the major energy of interior sound is concentrated in low frequencies, with overall interior A-weighted sound pressure levels at wide-open throttle typically ranging between 45 and 80 dBA. Qatu (2012) concluded that tire noise dominates cabin sound at constant speeds in the range of 40–85 km/h, while wind noise becomes prominent at constant speeds above 75 km/h. Zeitler and Zeller (2006) found that sound discomfort in CVs is mainly associated with constant speed noise, and occupants often perceive sound during acceleration as contributing to the sportiness of the vehicle.

Ride comfort in electric vehicles (EVs) presents unique challenges and opportunities compared to CVs. The absence of a torque converter can lead to torsional vibrations that significantly impair ride comfort (Karikomi et al., 2006). He et al. (2010) found that, in certain EVs, vibrations were more pronounced compared to combustion-engine vehicles (CVs) due to resonance between the traction motor and the vehicle driveline.

Sound perception inside EVs also differs from that in CVs. Fang et al. (2015) found that in EVs, the main energy of A-weighted sound is concentrated between 1000 and 2500 Hz. Furthermore, Qin et al. (2020) noted that sounds generated by electrical components in EVs can be more noticeable than in CVs due to the lack of internal combustion engine noise, while Berge and Haukland (2019) indicated that tire noise becomes audible at speeds around 20 km/h in EVs. He et al. (2010) concluded that at low speeds, sound radiated by the differential is the primary source of noise, while at high speeds, noise from the electric motor predominates.

Recent research has investigated the application of advanced technologies to predict and assess ride comfort. For instance, driving simulators have been utilized to study ride comfort in a controlled and safe environment (Bellem et al., 2017). By providing a consistent and adjustable setting, simulators allow researchers to explore various aspects of ride comfort without the variability present in real-world conditions. Different types of driving simulators, such as shaker-based and hexapod-based configurations, have been used to analyze vibrations. A review by (Xue et al., 2023) has systematically outlined numerous studies investigating the impact of amplitude, frequency, and direction of vibration on human responses using shaker-based simulators. Hexapod-based driving simulators offer a broader range of motion compared to conventional systems. These simulators can replicate dynamic driving conditions more accurately, making them ideal for studying complex motion patterns encountered in real-world scenarios (Bellem et al., 2018). Technological advancements have further enhanced hexapod systems, enabling the simulation of multidirectional movements that closely mimic actual driving experiences (Bellem et al., 2017).

Machine learning has emerged as a powerful tool in ride comfort studies, offering new avenues for data analysis and prediction. This technology allows researchers to handle vast amounts of data and uncover complex patterns that traditional methods might miss. By using machine learning algorithms, researchers can analyze various factors influencing ride comfort, such as vibration, noise, and seat ergonomics, and predict occupant comfort levels with greater accuracy. For example, a study by (Cieslak et al., 2020) demonstrated how machine learning models could effectively predict ride comfort by analyzing occupant anthropometric data and measured vibrations. Similarly, Nguyen et al. (2021) predicted real-time comfort ratings of bus occupants using collected seat vibrations and driving speeds. The integration of machine learning not only enhances the precision of comfort predictions (Nguyen et al., 2021) but also aids in the development of adaptive systems that can adjust vehicle settings in real-time to optimize comfort (Yu et al., 2023).

Most previous studies have investigated the influence of single factors, such as sound or vibration, under specific scenarios like constant speed. However, real-world rides involve various simultaneous inputs that vary across different driving scenarios and vehicles. Wang et al. (2020b) summarized that human responses to sound and vibration vary depending on their frequency and amplitude, and these factors can interfere with each other. Moreover, few studies have examined how sound and vibration influence perceived ride comfort in EVs. The differences in overall ride comfort between CVs and EVs have yet to be clearly identified.

Additionally, while driving simulators have been utilized to generate various vibrations in laboratory studies and replicate dynamic driving conditions and complex motion patterns in the real-world, comprehensive assessments of the overall benefits and challenges associated with employing driving simulators in studies regarding ride comfort have been infrequent. Moreover, previous research has often overlooked the distinctions in methodological approaches between studies utilizing driving simulators and those employing real vehicles.

Furthermore, some frameworks of machine learning used in previous studies were limited by small data volumes, hindering the models' ability to learn data diversity, affecting their generalization and robustness. The widely used evaluation metrics vary with different rating scales, complicating comparisons across studies. Additionally, some studies lack cross-validation, essential for assessing and ensuring generalization capability, leading to potential overfitting. Moreover, the absence of model interpretation reduces trust, hinders optimization, and makes it harder to detect biases and errors, increasing the risk in real-world applications.

In summary, field tests, driving simulators, and machine learning each offer unique strengths and limitations in the study of ride comfort. Field tests provide essential real-world data, driving simulators offer controlled environments for detailed studies, and machine learning enables sophisticated data analysis and prediction. However, these methods face significant limitations: field tests are resource-intensive, driving simulators may not fully replicate real-world conditions, and machine learning models struggle with small data volumes and a lack of cross-study comparison, reducing their reliability and applicability.

1.2 Aim and research questions

The five-year research project aims to provide the automotive industry with targets and guidelines for developing future mobilities characterized by high comfort levels. The central hypothesis underpinning this work is that single factors, such as sound or vibration, influence occupants' perceptions differently depending on the driving scenario (e.g., road profile and speed). This variability can be leveraged to reduce experienced discomfort.

Research question 1: What is the definition of ride comfort from occupants' perspective?

The first research question focuses on defining ride comfort from the occupant's perspective and the methodology used to identify factors significantly affecting overall ride comfort. Passenger car occupants are exposed to various factors and interact with the vehicle's components during the ride. These inputs are perceived and responded to by the occupants. Investigating these passenger experiences helps to delineate what constitutes ride comfort. Moreover, examining both subjective assessments and objective measurement data across different scenarios enhances our understanding of how various factors influence perceived ride comfort. It is important to clarify that defining ride comfort in this context involves understanding the interplay of sensory experiences, physical interactions, and emotional responses that together create the overall perception of comfort for the occupant.

Research question 2: How is ride comfort influenced by sound and vibration?

The second research question aims to specify the influences of sound and vibration on ride comfort. Since sound and vibration vary with different driving scenarios, the resulting ride comfort experienced by occupants also varies. A methodology that correlates subjective assessments with objective measurements of sound and vibration is necessary to determine how occupants' experiences change in response to variations in sound and vibration.

Research question 3: How could advanced technology be utilized in ride comfort, specifically vibration discomfort prediction and assessment?

The third research question explores the application of advanced technologies in ride comfort studies. This includes evaluating the benefits and constraints of high-level driving simulators and investigating feasible and unfeasible study designs in user experience research. The goal is to propose guidelines for using high-level driving simulators to study user-experienced ride comfort. Additionally, this question aims to develop a framework addressing the challenges of studying ride comfort using machine learning, including limited data availability, model interpretation, and cross-study comparisons. By using data augmentation and proposing suitable performance metrics, the framework seeks to enhance the accuracy and reliability of ride comfort prediction models, provide insights into influencing factors, and ensure accurate model evaluation and meaningful comparisons between models.

This thesis analyses the accumulated literature concerning the initial phases of research development. It begins by identifying the factors influencing both ride comfort and discomfort. Subsequently, the thesis aims to establish guidelines and frameworks for integrating advanced technologies in ride comfort studies. This approach facilitates a thorough exploration of the underlying causes of ride comfort issues and offers practical methodologies for their investigation and improvement.

The thesis includes five papers. Paper A analyses previous studies to investigate the definition of ride comfort and the impact of vibration on discomfort. Papers B and C examine the effects of sound and vibration under various driving scenarios in both combustion engine and electric vehicles, where the correlation between subjective assessments of ride comfort and objective measurements of sound and vibration is discussed to enhance the understanding of perceived ride comfort. Paper D outlines guidelines for designing ride comfort studies using advanced driving simulators, and Paper E presents a framework for predicting ride comfort based on measured sound, vibrations, and occupant demographics. Figure 1 illustrates the connections between research studies, papers, and research questions in this thesis.

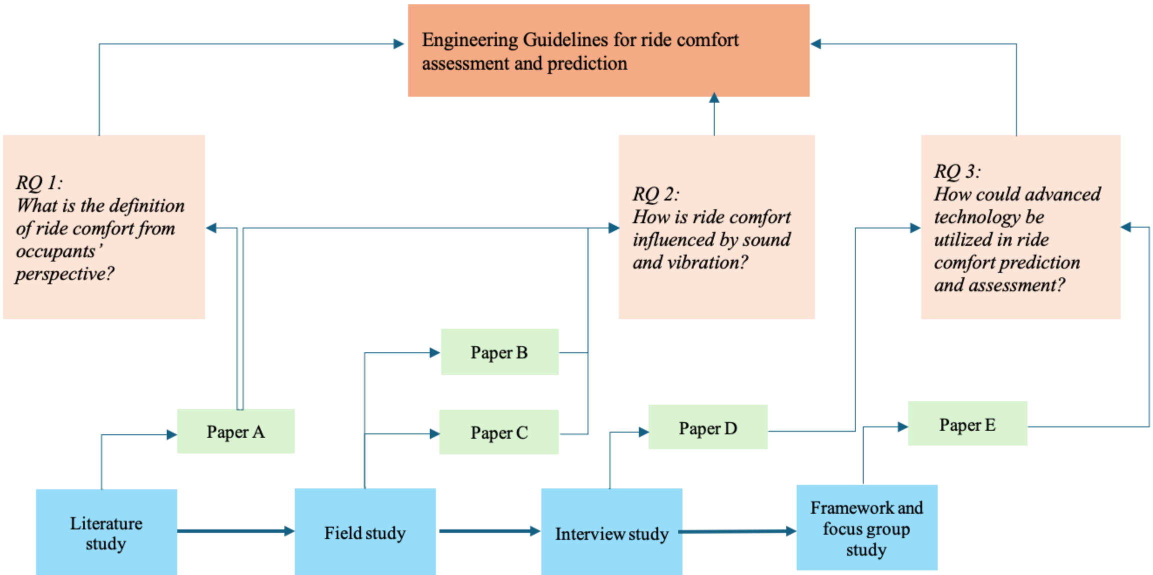

Figure 1. Connections between research studies, papers, and research questions.

1.3 Outline

The thesis is organized into three main sections. The first section introduces the topic and comprises literature reviews along with a discussion on the methodology, covered in Chapters 1, 2, and 3. The second section delves into the ride comfort experiences of front-seat occupants in both combustion and electric vehicles, as presented in Chapter 4.1. This section also explores the application of advanced driving simulators (Chapter 4.2) and machine learning techniques (Chapter 4.3) in studies of vibration annoyance. The third section addresses the research questions in Chapter 5 and outlines guidelines for conducting field studies, driving simulator studies, and machine learning studies in Chapter 6. Chapter 7 provides an examination of the strengths and weaknesses of the study methods used, as well as the generalizability of the study's findings. The thesis wraps up with a summary of the results in Chapter 8.

Chapter 2: Theoretical framework

The theoretical framework encompasses sound, vibration, and human factors. It includes reviews of human responses to sound and vibration in both laboratory and real-world vehicle settings and examines the influence of sound and vibration on ride comfort. Additionally, it explores the utilization of driving simulators and machine learning techniques in studying and predicting ride comfort, providing an approach to understanding and enhancing occupant experiences.

2.1 Comfort and discomfort

The concepts of comfort and discomfort in the vehicular context have been extensively studied, yet they remain inherently subjective and multifaceted.

Comfort is generally defined as a pleasant state or relaxed feeling of a human being in reaction to its environment, often resulting from the harmonious integration of factors such as seat ergonomics, thermal environment, and acoustic conditions (Grandjean and Kroemer, 1997). Grandjean and Kroemer (1997) present a comprehensive overview of comfort, emphasizing the importance of ergonomic design in mitigating physical strain and enhancing overall well-being. The interplay between seat design, posture, and anthropometric factors is highlighted as crucial to achieving comfort in automotive settings.

In contrast, discomfort is characterized by sensations of unease or stress, often attributed to prolonged exposure to adverse physical conditions or sensory stimuli (Helander and Zhang, 1997). Branton (1969) provides an early examination of discomfort, focusing on the negative impacts of poor seating design and improper posture. His research identifies key discomfort factors, including pressure points, restricted movement, and inadequate support, which can lead to musculoskeletal issues over time. Furthermore, Corlett and Bishop (1976) discuss the role of seating postures in discomfort, illustrating how prolonged and awkward postures can lead to increased musculoskeletal discomfort. Griffin and Erdreich (1991) moreover provide a comprehensive framework for understanding human vibration and its impact on discomfort, where they distinguish between whole-body vibration, experienced through the seat, and localized vibrations, felt in the hands or feet.

These foundational studies underscore that comfort and discomfort are influenced by a complex interplay of factors, requiring a holistic approach to their assessment and mitigation in the automotive industry. Zhang et al. (1996) suggested a conceptual model of comfort and discomfort, which has the transitions between comfort and discomfort in the intersection of two orthogonal axes, while Makris et al. (2024) proposes a holistic model for car ride comfort, categorizing influential factors into physical, psychological, and functional aspects.

Measuring comfort and discomfort involves both subjective assessments and objective metrics. Subjective assessments often rely on self-reported questionnaires and interviews. Tools like the self-reported questionnaires (Hart, 1988) and the Likert scale (De Looze et al., 2003) are widely used to gather occupant feedback on various comfort aspects such as seating, noise, and vibration. Objective measurements typically involve quantifying physical parameters that influence comfort. For instance, whole-body vibrations can be measured on the seat and floor, capturing data on the frequency and amplitude of vibrations (ISO 2631-1, 1997). Similarly, noise levels are commonly measured to quantify the acoustic environment inside the cabin (Sheng, 2012).

Recent studies have concluded that shorter studies (around three minutes) can capture average postures and seatbelt fit, while longer studies are required to observe posture variations, particularly for individuals with unique body shapes. Discomfort in areas like the back and buttocks increased similarly in both scenarios after 15 minutes, with slumped postures contributing to back discomfort over time. The stationary scenario led to more awareness and boredom, while the driven scenario allowed for more natural movements (Makris, 2023).

2.2 Human responses to vibrations

Vibration is a critical factor affecting perceived ride comfort, as it can degrade overall comfort, induce motion sickness, impede activities during the ride, and, over the long term, lead to impaired health (Wang et al. 2020b). Passenger car occupants experience both whole-body vibrations (WBV) and local vibrations. WBV refers to vibrations transmitted to the body through a supporting surface, whereas local vibrations are transmitted to specific body parts through contact areas (Griffin and Erdreich, 1991).

Von Gierke and RR (1961) discovered that seated humans are more sensitive to WBV than local vibrations below 20 Hz, noting that above 20 Hz, vibrations are attenuated by the body's soft tissues. Griffin and Erdreich (1991) observed that above 20 Hz, vibration primarily affects areas in contact with the vibrating surface, attributing discomfort at higher frequencies to resonance and the biodynamic response of various body parts. Vibration in the 100–300 Hz range, particularly transmitted through the steering wheel, has been linked to hand discomfort (Giacomin and Woo, 2005; Morioka and Griffin, 2009).

Figure 2 provides a summary of human responses to vibration. As depicted, vibration characteristics include frequency, magnitude, direction, and duration, while individual characteristics encompass posture, orientation, age, gender, and anthropometry (Griffin and Erdreich, 1991).

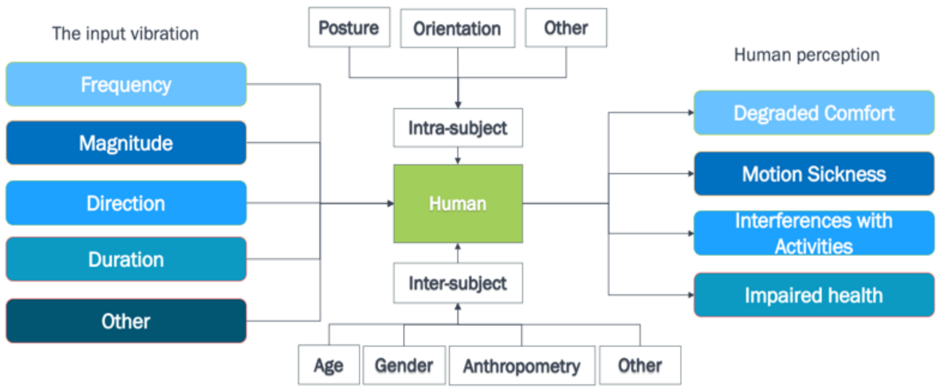

Figure 2. Factors that affect human perception of vibration.

Human sensitivity to vibration discomfort varies with frequency, magnitude and direction as illustrated in Figure 3. Higher frequencies require greater vibration levels to produce the same discomfort. The effects of frequency on perceived comfort are influenced by vibration magnitude and direction (Morioka and Griffin, 2006), body posture (Nawayseh and Griffin, 2012), orientation (Huang and Griffin, 2009), and individual demographics (Toward and Griffin, 2011). Vertical vibrations are perceived more acutely at low frequencies, with peak sensitivity around 5 Hz, attributed to the body's resonance behavior (Zhou and Griffin, 2014). Low-frequency vertical vibrations (below 10 Hz) primarily affect the lower abdomen, lower thighs, and ischial tuberosities, whereas higher frequencies impact the spine, head, neck, shoulders, and chest (Arnold and Griffin, 2018). Sensitivity to longitudinal and lateral vibrations is highest around 2–3 Hz and 1–2 Hz, respectively, decreasing with higher frequencies due to changes in the affected body parts (Morioka and Griffin, 2006). Discomfort from longitudinal vibrations diminishes with frequency, particularly in the upper torso, while lateral vibrations primarily affect the shoulders, chest, lower abdomen, ischial tuberosities, and lower thighs (Arnold and Griffin, 2018).

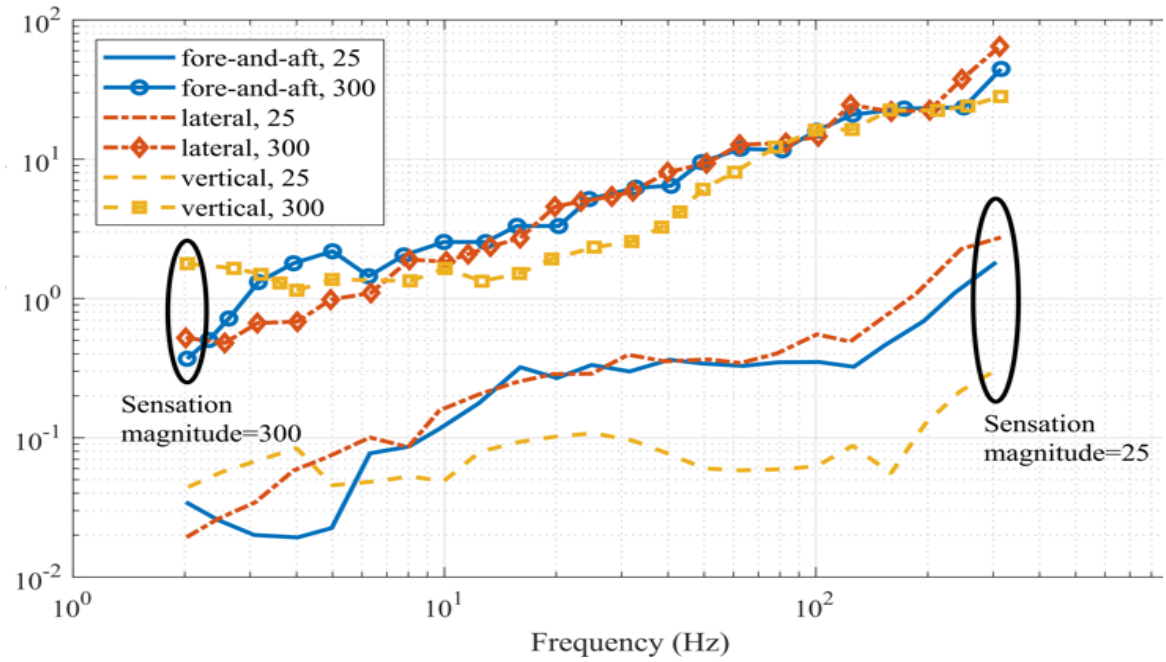

Figure 3. Equivalent comfort contours for sensation magnitudes of 25 and 300. Figure adapted from (Morioka and Griffin, 2006).

Vibration magnitude is another influencing parameter on perception sensitivity. Morioka and Griffin (2006) found that sensitivity to vertical vibrations between 10–20 Hz increases more slowly with higher vibration magnitudes, with the frequency of greatest sensitivity decreasing as vibration levels rise. Arnold and Griffin (2018) noted that higher vibration levels shift discomfort from the lower body to the shoulders and chest. Horizontal vibration sensitivity also depends on vibration magnitude, with higher frequencies resulting in less sensitivity (Morioka and Griffin, 2006). Primary contact areas are most affected by horizontal vibrations, leading to consistent discomfort locations as vibration magnitude increases (Arnold and Griffin, 2018).

Posture and orientation significantly influence vibration discomfort perception. Different postures and orientations, such as sitting upright (Toward and Griffin, 2011) or lying down (Toward and Griffin, 2009), result in varied biodynamic responses (Morioka and Griffin, 2006). With increased back inclination, human sensitivity to vertical vibrations reduces, especially at resonance frequencies (Basri and Griffin, 2012). For recumbent subjects, back sensitivity is lower compared to other body parts (Huang and Griffin, 2009). Standing subjects exhibit similar vertical apparent mass resonance frequencies to seated subjects, indicating similar dynamic upper body mechanisms (Matsumoto and Griffin, 1998).

Inter-subject variables like age, gender, and anthropometry significantly influence vibration discomfort perception, with effects varying by vibration magnitude (Toward and Griffin, 2011). Age correlates with increased resonance frequency and peak magnitude (Toward and Griffin, 2011), with seniors more likely to lean forward in car seats (Osvalder et al., 2019). Gender differences in vibration response are also noted, with males showing higher normalized apparent mass at resonance frequencies because males had greater body weight supported by the reclined backrest (Toward and Griffin, 2011).

2.3 Human responses to sounds

Sound plays a crucial role in human comfort and well-being (Fastl and Zwicker, 2007). As modern passenger cars have become quieter, the focus on sound quality as a component of ride comfort has intensified (Sheng, 2012). Studies consistently show that equivalent A-weighted sound pressure levels correlate with sound annoyance, particularly when the sound initially begins (B. Berglund et al., 1990; U. Berglund et al., 1976; Beutel et al., 2016). However, A-weighting alone does not fully capture humans' complex responses to sounds (Fastl and Zwicker, 2007; Moore, 2012). Human perception of sound is influenced by time variations in sound (Ishiyama and Hashimoto, 2000), the energy of low-frequency components (Nilsson, 2007) and sound characteristics (Fastl and Zwicker, 2007).

Figure 4 summarizes how sound affects human auditory and cognitive systems (Fastl and Zwicker, 2007; Moore, 2012). Although sound assessments typically rely on physical measurements like frequency and sound pressure level, the human auditory and cognitive systems filter the final evaluation. This necessitates mapping physical measurements to psychoacoustic metrics such as loudness and sharpness, which help relate sound properties to perceptions like annoyance and sleep disturbance (Fastl, 2006). Responses to sound vary with age, gender, and psychological factors, such as age, gender (Stelrnachowicz et al., 1989), expectations and experiences (Skagerstrand et al., 2017).

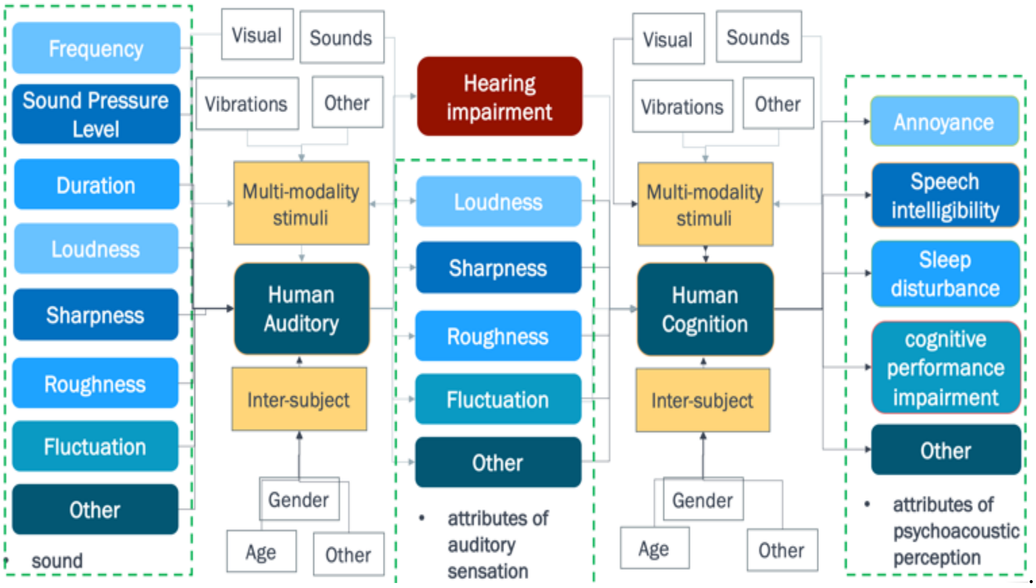

Figure 4. The factors that affect human perception of degraded comfort due to sound.

Sound annoyance has been related to disliking the source, distraction (Guski et al., 1999), unpleasantness, exhaustion (Öhrström et al., 2006), sleep disturbance and other stress-related symptoms (Bakker et al., 2012). Jeon et al. (2010) found that perceived sound discomfort is strongly related to annoyance, which depends on properties like sound level, frequency spectrum (Ouis, 2001), loudness, sharpness, fluctuation strength (Hall et al., 2013) and sound context (Genell et al., 2006), as well as the individual attitude toward the sound (Ouis, 2001).

Sound annoyance increases with sound pressure level (Subedi et al., 2005). Ishiyama and Hashimoto (2000) found that annoyance grew more quickly above 60 dB(A). Skagerstrand et al. (2017) suggested correlations between "comfortably loud/not annoying," "slightly annoying," and "very annoying" for sounds with SPLs between 48-55 dB, 56-65 dB, and above 79 dB, respectively.

Annoyance from sound is amplified by low-frequency exposure because low-frequency sound caused additional vibrations in the body, such as the chest (Pelmear and Benton, 2003) and abdomen (Takahashi et al., 2002). Higher frequencies are less likely to cause distress. The relationship between annoyance and sound characteristics is nuanced, with tonal sounds generally perceived as more bothersome than untoned ones (Jeon et al., 2010).

The balance between high and low-frequency sounds also affects annoyance perception. Genell et al., (2006) found that listeners were more annoyed by sounds lacking higher frequencies than by balanced frequency content, while Alayrac et al. (2011) indicated that pure tones were judged less annoying than broadband noise. Subedi et al. (2005) furthermore showed that annoyance from combined tone components depended on level differences and frequency separation within the tones. Low frequency dominated broadband noise was more annoying (Persson Waye and Rylander, 2001b), whereas pure tones were less annoying (Subedi et al., 2005).

Sound annoyance tends to increase with loudness (Skagerstrand et al., 2017), as indicated by both mean and maximum loudness levels with mean (Glasberg and Moore, 2002) and the maximum loudness value (Zorilă et al., 2016) serving as indicators. Besides loudness, sharpness is crucial for sound annoyance (Fastl and Zwicker, 2007), particularly for sounds above 1000 Hz, where irritation grows with higher sound pressure levels (Ishiyama and Hashimoto, 2000).

Research indicates that tonal sounds are perceived as more annoying than non-tonal ones (Jeon et al., 2011). The annoyance intensifies with the number of tonal components and decreases as these components are reduced (Landström et al., 1995). Dickson and Bolin (2014) found that reducing tonal components had a greater impact on reducing instantaneous annoyance than increasing them.

Even when loudness remains constant, factors such as fluctuation strength and roughness can impact sound annoyance (Moorhouse et al., 2008). Di et al. (2011) found that frequency-modulated sound influenced annoyance perception, decreasing as modulation frequency increased, and increasing as modulation sound pressure level rose when it is above 30 dB.

Human perception of sound involves sensory, cognitive, and emotional aspects (Zeitler et al., 2004). Unidentifiable sounds are considered more annoying (Ellermeier et al., 2004), while sounds perceived as pleasant are rated less bothersome despite higher sound pressure levels (Yang and Kang, 2005). Sounds' meanings influence their evaluation. Nature sounds can reduce perceived annoyance and loudness (Bolin et al., 2010).

Expectations about sound affect assessments of loudness and annoyance (Skagerstrand et al., 2017). Individuals who depend on a sound are often less irritated by it (Miedema and Vos, 1999). For instance, vehicle noise is considered less annoying to occupants in vehicles than when heard in an apartment setting (Genell et al., 2006).

Demographic factors, such as gender, show minimal influence on annoyance from steady sounds (Janssen et al., 2014), although age may affect responses, with teenagers exhibiting higher discomfort compared to seniors, who are less troubled by nature and human activity sounds (Moorhouse et al., 2008).

2.4 Field studies of vibrations in vehicles

Vibration levels in a vehicle's seat, floor, and steering wheel are impacted by factors such as road profile, driving speed, and vehicle type. Adam and Jalil (2017) found that floor vibrations were generally greater than those in the seat of the same car. At high speeds or on rough roads, vibrations transmitted to the seat, backrest, and steering wheel were greater in the vertical (Kaderli and Gomes, 2015) and lateral (Lin et al., 2006) directions than in the longitudinal direction.

The most significant vibrations in the seat occur at contact points with the human body, such as beneath the knee (Mansfield, 2001), the back of the thighs, (Wu et al., 1999), and the buttocks (Kilincsoy et al., 2016). These vibrations are primarily concentrated below 20 Hz in the lateral and vertical directions (Griffin and Erdreich, 1991) and below 30 Hz in the longitudinal direction (Nawayseh, 2015).

Rakheja et al. (2002) indicated that in passenger cars, backrest inclination and seat height can alter the angle between the upper and lower body and change the occupant's knee height. They also found that the driver's choice of steering-wheel grip posture led to other positional differences.

Research by van Veen et al. (2015) suggested that macro-movements, or frequent and distinct changes of posture, could enhance perceived comfort due to the pleasant stimulation of tactile sensation. Beach et al. (2005) observed that such movements help reduce discomfort, especially during prolonged sitting, and that posture changes were more common when the vehicle was stationary.

Kyung and Nussbaum (2009) found that driving postures vary with age, gender, and anthropometry. Differences in elbows, hips (Kyung and Nussbaum, 2009), and spine angles (Bohman et al., 2019; Osvalder et al., 2019) are notable between younger and older occupants. Kyung and Nussbaum (2009) concluded that gender influences the angle of the left elbow during driving, while body height affects the angles of the left ankle, left hip, and neck.

2.5 Field studies of sounds in vehicles

Qatu (2012) categorized vehicle interior noise according to various root causes: powertrain/driveline noise, tire noise, wind noise, brake and chassis noise, squeak and rattle, and electromechanical sounds. Zeitler and Zeller (2006) concluded that experienced sound discomfort in a vehicle was dominated by sound at constant speed and wind noise. In addition, engine sound contributes significantly to perceived noise during acceleration and has been associated with the sportiness of the vehicle. Without the masking effect of the combustion engine, noises caused by components such as tires, the transmission and the HVAC system become more audible and may induce annoyance (Sarrazin et al., 2012).

Tire noise

Sandberg and Ejsmont (2002) found that at speeds between 30–100 km/h, tire noise dominated the interior sound in passenger cars, especially under cruising or partial throttle conditions. Sandberg (2001) indicated that tire noise increases with speed. In electric vehicles, reduced powertrain noise makes tire noise a more significant contributor to total noise, even at lower speeds.

Hoffmann (2016) identified two main sources of tire noise: tire vibration and air pumping. Tire vibration is caused by variations in the contact area geometry between the tire and the road. Vieira (2020) showed that the noise caused by tire vibration covers a wide frequency range, 100–1200 Hz. Low-order modes of tire noise, caused by time-varying contact shapes, dominate the radiated sound around 1000 Hz (Kropp et al., 2012). Air interference with the tire surface and tread produces noise ranging from 600 to 2500 Hz (Vieira, 2020). Feng et al. (2009) observed sharp peaks in the 190–250 Hz frequency range due to tire cavity resonance. The peak frequency of cavity noise depends on tire load and vehicle speed (Qatu et al., 2009), explained by the load breaking the tire's symmetry under rolling conditions (Feng et al., 2009).

Wind noise

Talay and Altinisik (2019) concluded that as driving speed increases, structure-borne noise becomes less significant compared to airborne wind noise generated by airflow around the vehicle. Qatu et al. (2009) found that wind noise usually dominated interior noise above 90 km/h. Talay and Altinisik (2019) indicated that the perceived wind noise sound pressure level at the driver’s left ear increases with frequencies up to around 1000 Hz, then drops significantly. Yingjie et al. (2019) showed that wind noise from the front side window is greater than that from the rear side window at most frequencies, with peak noise levels occurring around 260 Hz and 200 Hz, respectively.

Powertrain/driveline sound

Qatu et al. (2009) indicated that powertrain noise is noticeable under all driving conditions in combustion-engine cars and can be more significant than tire noise at speeds below 40–50 km/h. Occupants expect to hear powertrain sounds during idling, cruising, and coasting, with most interior powertrain noise between 50–80 dB(A) for passenger cars and 50–85 dB(A) for midsize SUVs.

Lennström and Nykänen (2015) concluded that driveline sound in electric cars differs significantly from that in combustion cars. Low-frequency firing orders, mechanical noise, and engine noise in combustion cars are replaced by high-frequency tones generated by electromagnetic forces and gear meshing. Driveline sound in electric cars is usually at a lower level but perceived as more annoying than the powertrain sound of combustion cars.

Other sounds

In passenger cars, occupants can perceive various sounds, such as HVAC noise, influencing ride comfort and perceived quality. The impact of HVAC noise is intertwined with changes in the vehicle's interior thermal comfort due to the interaction between thermal and acoustic perceptions (Roussarie et al., 2005). Key psychoacoustic models used to characterize the perception and quality of HVAC noise include loudness, sharpness, prominence, spectral composition, and tone-to-noise ratio (Leite et al., 2009).

Qin et al. (2020) identified that structure-borne sound related to the combustion-engine firing cycle at 20–200 Hz is the dominant cause of sound annoyance during start/stop. In electric cars, start/stop sounds are often distinctly designed to provide notification information (Frank et al., 2014).

In addition to these, information and warning sounds also play a crucial role in passenger cars. These sounds are designed to provide drivers with significant information regarding vehicle status or safety alerts. For instance, (Edworthy and Stanton, 1995) emphasize the importance of designing effective auditory displays for information and warning purposes in vehicles. Similarly, Edworthy and Hellier (2000) discuss how auditory warnings must be perceptible, interpretable, and timely to be effective, highlighting their critical role in enhancing vehicle safety and communication.

2.6 Utilization of advanced technologies

This session examines the role of advanced technologies, such as driving simulators and machine learning, in automotive research. These tools enhance the study of ride comfort by offering detailed insights into user performance and experience.

Driving simulators are instrumental in studies of occupant experience and ride comfort, particularly with automated cars (Gerber et al., 2019) or intelligent vehicles (Caird et al., 2008). Driving simulators offer several advantages. Firstly, simulators offer a controlled (Hartwich et al., 2019) and safe (Manawadu et al., 2015; Schmidt et al., 2016) testing environment for assessing various aspects of vehicle technologies. Secondly, driving simulators enable the repetition of experiments under consistent conditions, ensuring reliable data collection and analysis. This repeatability is crucial for validating and fine-tuning vehicle control algorithms and functionalities (Hock et al., 2018; Yun et al., 2019). Various simulator configurations, such as shaker-based and hexapod-based driving simulators, have been employed to delve into the nuances of ride comfort.

Shaker-based simulators generate specific vibrations for research, offering precise frequency control up to 200 Hz (Bellmann, 2002). Despite advancements, they are limited in motion capabilities, affecting their ability to simulate dynamic driving conditions and real-world road irregularities accurately (Xue et al., 2023). This limitation can reduce the immersive experience they provide and may affect the ecological validity of studies. Hexapod-based simulators offer a broader range of motion, facilitating a more detailed simulation of dynamic driving conditions and closely mirroring real-world scenarios (Bellem et al., 2018). These systems improve the realism of simulations by accurately replicating road irregularities, thereby enhancing the study of ride comfort. However, the extended range of motion can increase the risk of motion sickness in participants, potentially impacting the validity of study outcomes (Bellem et al., 2017).

Integrating machine learning into ride comfort evaluations, particularly for vibration-related discomfort, has emerged as an effective approach to improve traditional methodologies (Fitzpatrick et al., 2016). Figures 5, 6 and 7 illustrate several frameworks used in previous studies using machine learning. One common framework (Gao et al., 2010; Singh et al., 2023; Taghavifar and Rakheja, 2018), as depicted in Figure 5, comprises data collection and modeling, encompassing feature engineering, selection of appropriate model architecture, training, testing, and evaluation of the model's performance. Another widely utilized framework (Cieslak et al., 2020; Kolich et al., 2004; Nguyen et al., 2021) is illustrated in Figure 6, encompassing data collection, modeling, and model interpretation. Additionally, some studies (Du et al., 2021; Yu et al., 2023) have incorporated a framework that includes data augmentation to address the limitations of dataset size as shown in Figure 7.

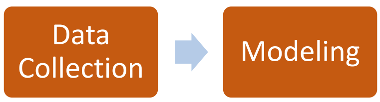

Figure 5. The framework utilized in study (Gao et al., 2010; Singh et al., 2023; Taghavifar and Rakheja, 2018)

Figure 6. The framework utilized in studies (Cieslak et al., 2020; Kolich et al., 2004; Nguyen et al., 2021)

Figure 7. The framework utilized in studies (Du et al., 2021; Yu et al., 2023)

Data augmentation methods, such as those implemented by (Du et al., 2021; Yu et al., 2023), help enhance dataset size and variability. Techniques like down-sampling, channel replacement (Yu et al., 2023), data segmentation, and resampling (Du et al., 2021) are employed to increase data robustness. These methods expand the dataset effectively but require balancing data integrity with variability.

Feature engineering transforms raw data into meaningful features, crucial for improving model performance in ride comfort studies, especially concerning vibration annoyance (Nguyen et al., 2021). Key features extracted include weighted vibrations, root mean square (RMS) vibrations, and demographic data such as weight, gender, and posture (Taghavifar and Rakheja, 2018).

Machine learning models, particularly Artificial Neural Networks (ANNs), are widely used for their ability to capture complex relationships within vibration data. ANNs are flexible and adaptable, handling high-dimensional inputs effectively (Nguyen et al., 2021). However, they require significant computational resources and careful hyperparameter tuning (Du et al., 2021). Besides ANNs, Gradient Boosting Machines (GBM) (Sarker, 2021) and Random Forest (RF) (Singh et al., 2016) are powerful techniques for analyzing sound and vibration data. GBMs, as ensemble learning methods, build sequences of weak learners like decision trees to enhance predictive accuracy by minimizing prior errors (Sarker, 2021). While effective with various data types, GBMs are computationally intensive, require significant training time, and are sensitive to hyperparameter tuning, posing challenges in interpretation (Yu et al., 2022). In contrast, RF builds multiple decision trees and merges their outputs to increase accuracy and stability (Singh et al., 2016). RF's robustness against overfitting, ability to handle both categorical and numerical data, and feature selection capability make it suitable for complex vibration signal studies, such as fault diagnosis. Despite these strengths, RF models can be computationally expensive, may suffer from a bias-variance tradeoff, and can be less straightforward to interpret compared to simpler models (Li et al., 2016).

Evaluating model performance and generalization is essential for assessing vibration annoyance. Various studies utilize metrics like mean squared error (MSE) (Singh et al., 2023; Taghavifar and Rakheja, 2018), mean absolute error (MAE) (Singh et al., 2023), and the coefficient of determination (R^2) (Nguyen et al., 2021; Kolich et al., 2004) to measure model accuracy and reliability. Sensitivity analysis is employed to determine the impact of different variables on model outcomes, aiding in feature prioritization and model refinement (Cieslak et al., 2020). Though insightful, sensitivity analysis can be computationally demanding and may not always generalize across models or datasets (Kolich et al., 2004).

While MSE, MAE, and R^2 are commonly used in regression tasks, different metrics, such as recall, precision and F1 score, are applied in classification tasks. In the context of classification tasks, fundamental concepts such as positive (P), negative (N), and true positive (TP) were pivotal in guiding this selection. Positive instances represent the presence of the condition or event of interest, while negative instances denote its absence. True positive, specifically, signifies instances where the model correctly identifies the presence of the condition, highlighting its capacity for accurate detection (Yacouby and Axman, 2020). The elucidation of positive (P), negative (N), and true positive (TP) is delineated in Figure 8. Recall, as depicted in Eq.4, quantifies the proportion of true positive instances correctly identified by the model out of all actual positive instances. Precision, as shown in Eq.5, measures the proportion of true positive instances correctly identified by the model out of all instances predicted as positive (PP). These metrics provide complementary insights into the model's ability to minimize missed detections (false negatives) and incorrect identifications (false positives) (Yacouby and Axman, 2020).

$$recall = \frac{TP}{P} \qquad \text{Eq.4}$$

$$precision = \frac{TP}{PP} \qquad \text{Eq.5}$$

where TP represents true positive, PP represents predicted positive, and P represents positive.

		Prediction condition	
	Total = P+N	*Predicted Positive (PP)*	*Predicted Negative (PN)*
Actual condition	*Positive (P)*	Ture Positive (TP)	False negative (FN)
	Negative (N)	False positive (FP)	True negative (TN)

Figure 8. The definitions of positive, negative, predicted positive and true positive

In addition to recall and precision, the F_1 score serves as a composite metric that balances both metrics, thereby offering an evaluation of model performance (Yacouby Reda and Axman Dustin, 2020). As illustrated in Eq.6, the F1 score represents the harmonic mean of recall and precision, synthesizing their strengths into a single metric. By considering both recall and precision simultaneously, the F1 score provides a robust assessment of the model's ability to achieve a balance between identifying relevant instances and minimizing false alarms.

$$F_1 = \frac{2}{recall^{-1} + precision^{-1}} \qquad \text{Eq.6}$$

Feature importance analysis is another technique widely used in machine learning to identify which features are most influential in the decision-making process of the model, providing insights and interpretation of model behavior. Tree-based models like RF and GBM inherently provide feature importance scores based on how much they reduce impurity at each split (Bickel et al., 2009). This intrinsic feature importance is direct and incurs no additional computational cost. Tree-based methods effectively capture non-linear relationships and feature interactions. However, these models can be biased toward features with high cardinality, and the importance scores may vary across different runs due to the inherent randomness in ensemble methods (Bickel et al., 2009).

Chapter 3: Research Approach and Methodology

This chapter introduces the overarching framework and methodologies employed in this thesis, aimed at assessing and improving ride comfort within the automotive industry. By integrating insights from existing literature, empirical data collected through structured field studies, and controlled laboratory experiments, the thesis seeks to establish rigorous methods for evaluating ride comfort.

The research in this thesis is based on two philosophical perspectives: positivism and interpretivism. The positivist approach seeks to objectively measure human responses through controlled experiments, focusing on observable data such as sound and vibration (Wang et al. 2020b). Conversely, interpretivism explores the psychological dimensions, gathering qualitative insights through interviews to understand how factors like age, gender, and past experiences influence individual reactions.

Papers B and C of this thesis employ a combination of positivist and interpretivist methodologies to explore occupants' perceptions of ride comfort, considering the impact of both vibrations and sounds. The research methodology included a test ride that integrated both subjective and objective measurements, supplemented by semi-structured interviews. Objective data, encompassing vibrations and sounds, were collected alongside subjective data, which involved participants' ratings on the experienced vibrations and sounds, as well as qualitative insights from interviews reflecting their experiences and perspectives. This combined methodological approach facilitates the identification of generalizable patterns while providing deeper insights into the nature of ride comfort. While the study found some alignment between objective measurements and subjective perceptions of both vibrations and sounds, it also revealed phenomena that could not be fully explained through biodynamic responses alone. Researchers continue to investigate how to explain critical consequences on ride comfort using objective measurements, focusing particularly on vibrations.

Recognizing the complexities of human perception, this thesis aligns with a constructivist and pragmatic worldview. It integrates subjective experiences with objective data, underscoring the importance of practical solutions within the automotive industry. The research begins with a literature review to establish a foundation, followed by field studies collecting real-world data on driving conditions and user experiences. The study further explores the role of advanced technologies, such as driving simulators and machine learning, in enhancing ride comfort evaluations. It discusses the benefits and limitations of using driving simulators and explores feasible study designs for integrating simulators into ride comfort studies. Moreover, the study proposes frameworks to address challenges like data limitations and model interpretation. Ultimately, by synthesizing insights from literature, empirical data, and laboratory experiments, this thesis offers methodologies for assessing and improving ride comfort, aiming to inform design practices in the automotive industry.

3.1 Literature study

The literature study is presented in paper A. To perform the literature study, a systematic approach was adopted to ensure a review of relevant research areas. Major academic databases such as IEEE Xplore, ScienceDirect, SpringerLink, PubMed, and Google Scholar were identified as primary sources for relevant literature. By targeting a wide range of scientific journals and conference proceedings without limiting the search to specific ones, the study ensured that all pertinent publications in the fields of sound and vibration / vehicle NVH, ergonomics, and comfort were considered.

A list of search terms and keywords related to ride comfort, vibration, sound, ergonomics, and vehicle NVH was developed. Keywords included "ride comfort", "whole-body vibration", "human responses to vibrations", "sound perception", "human responses to sounds", "vehicle noise", "vehicle vibration", "ergonomics in vehicles", "seat comfort", and "comfort assessment". Filters were applied to limit search results to peer-reviewed articles, review papers, and conference proceedings published within the last 50 years with a focus of the last 20 years, ensuring the inclusion of up-to-date research.

The selected literature was then organized into thematic categories based on the primary focus of the studies, such as "human response to vibrations in automotive vehicles", "evaluation of degraded comfort", "the frequency dependence of vibration discomfort", "the magnitude dependence of vibration discomfort", "the direction dependence of vibration discomfort", "the effect of intra-subject variables on vibration discomfort", "the effect of inter-subject variables on vibration discomfort", and "vibrations in real automotive vehicle".

Each article was critically analyzed to identify key findings, methodologies, and gaps in the existing research. Insights from different studies were synthesized to form a coherent understanding of the current state of knowledge in the areas of sound and vibration, ergonomics, vehicle NVH, and comfort. This analysis helped identify the influencing variables on perceived ride comfort and the influence of vibrations and sounds experienced in real-world vehicles, forming the basis for specific research questions and hypotheses to guide the subsequent phases of the thesis.

3.2 Field study

The field study is presented in paper B and C. A field study was conducted to investigate the experiences of vehicle occupants, focusing on both subjective assessments and objective measurements, especially in terms of sound and vibration influences.

The study involved ten participants who experienced eight typical driving scenarios in both a CV and an EV. After each scenario, subjective data were collected through questionnaires, followed by semi-structured interviews after completing all scenarios in each vehicle. Objective data related to sound and vibration were gathered using microphones and accelerometers, which were subsequently analyzed for each scenario. Detailed information on the test cars, tracks, scenarios, and participant demographics is available in Papers B and C.

Subjective data collection

The subjective data collection employed a five-point semantic scale, following the approach of (Carroll et al., 1959). Semantic scaling, widely used for rating stimuli based on perception during exposure, was applied using both unipolar scales (e.g., "not annoyed at all" to "extremely annoyed") and bipolar scales (e.g., "calm" or "alert"), depending on the variable of interest. Moreover, the ranking order method was utilized due to its effectiveness in making relative comparisons of several stimuli concerning a specific parameter, such as annoyance or discomfort (Namba and Kuwano, 2008). Participants ranked factors based on their influence on perceived ride comfort through questionnaires administered after each driving scenario. These questionnaires aimed to capture immediate impressions, thus directly linking specific stimuli to perceived comfort or discomfort. Participants rated various aspects such as annoyance caused by sound and vibration, concordance between sound and vibration, and the movement of specific body parts related to vibrations.

To gain deeper insights into user experiences, semi-structured interviews were conducted following the completion of all scenarios. These interviews included general questions about perceived comfort and discomfort, followed by specific queries for each scenario addressing participants' perceptions of sound, vibration, and induced body movements. Interviews covered topics such as general comfort and discomfort levels, specific annoyances related to sound and vibration, characteristics and concordance of sounds and vibrations, and body movements induced by specific driving conditions.
Interviewers utilized probing questions to elicit detailed participant experiences and identify causes of perceived discomfort. Participants were encouraged to reference their questionnaire responses and highlight any additional issues that arose during the test rides. The interview questions can be found in Table 5 of Paper B.

Subjective data analysis

Participants’ ratings of annoyance due to sound and vibration were evaluated across various driving scenarios and vehicle types. The study compared characteristics of sound, using positive-negative and alert-calm scales, as well as the relative movement of different body parts. Additionally, the degree of concordance between sound and vibration was assessed across different scenarios and vehicles.

Discomfort causes identified during interviews were categorized based on factors such as sound characteristics, vibration characteristics, concordance or discordance between sound and vibration, and induced body movements. Categories were further detailed, and the number of participants commenting on each factor was summarized to provide a further understanding of common discomfort sources.

Objective data collection

Instantaneous sound and vibration data were collected using sensors placed inside the vehicle cabin. Sound levels were measured at the front occupant’s left ear, while accelerometers recorded seat rail and armrest vibrations. Detailed sensor specifications and placements are provided in Table 6 of Paper B. Sound was sampled at 25,600 Hz and vibration at 1,024 Hz. Additionally, participants' body movements were recorded using two cameras: one mounted on the sun visor capturing lower body movements and another positioned at the front to capture upper body movements.

Objective data analysis

Sound data analyses involved calculating the A-weighted sound pressure level for each test scenario, considering the critical frequency range of human hearing (20 to 10,000 Hz). Specific segments of scenarios, such as engine start/stop, constant speed scenarios, long bumps, cornering, rough roads, speed bumps, and bridge joints, were focused on to capture representative data points.

Vibration data were analyzed using Fourier transform with a focus on the 0.5–50 Hz range, covering significant vibrations affecting the seat and armrest with high human sensitivity. Selected vibration signals were correlated with identified sound components to understand their impact on perceived comfort.

Videos capturing participants' body movements were reviewed, and movements were classified as either active or induced. Active movements included conscious posture adjustments and unconscious reactions, while induced movements were caused by vibrations, categorized into lateral and longitudinal upper and lower body movements.

3.3 Interview study regarding simulator utilization

This semi-structured interview study engaged 14 participants: six technicians (Te1–Te6) specializing in driving simulators, and eight researchers (R1–R8) experienced in their use. The technicians primarily focused on managing software, with three (Te1, Te5, and Te6) also handling hardware tasks. Participants were selected based on their extensive experience with high-level driving simulators, using a "snowball" method where existing participants recommended others.

The study aimed to understand the advantages and limitations of driving simulators compared to real vehicles, identify viable and non-viable research areas for simulators, and explore their application in ride comfort studies. Specific questions asked during the interviews are detailed in Table 1 of paper D.

Interview responses were video recorded, transcribed verbatim, and analyzed using content, thematic, and comparative analysis methodologies. The initial content analysis systematically reviewed the data to identify prevalent themes, keywords, and conceptual elements (Mayring, 2004). The subsequent thematic analysis involved coding the interview data based on identified themes, comparing simulator use to real cars, and exploring different study objectives (Mayring, 2004). This analysis phase also allowed for the emergence of new themes beyond predefined categories. Finally, comparative analysis examined discrepancies and commonalities in responses, deepening the understanding of various perspectives. By integrating these analytical methods, the aim was to derive insights crucial to the study’s overarching conclusions.

3.4 Development of framework for machine learning approach

The development of the machine learning approach is divided into two primary phases: the first involves the formulation of a framework that aims to leverage machine learning techniques to evaluate occupant experienced ride comfort, while the second entails the implementation of a focus group session to evaluate and discuss the proposed framework's efficacy and applicability.

Framework

The study is divided into two primary phases: the first involves the formulation of a framework that aims to leverage machine learning techniques to evaluate occupant experienced vibration annoyance, while the second entails the implementation of a focus group session to evaluate and discuss the proposed framework's efficacy and applicability.

Part I: Framework

- **Framework developing**

Through a literature review of the existing frameworks on vibration annoyance and ride comfort evaluation, several critical gaps were identified as outlined in the introduction. These gaps are limited data availability, challenges in model interpretability, challenges in generalization, and difficulties in cross-study comparisons. To address the identified gaps, the proposed framework should incorporate several key functions beyond the essential tasks of data collection and modeling. These additional functions include data augmentation, model interpretation, cross validation for model generalization capability assessment and evaluation methods for the capacity of cross-study comparisons. The proposed functions, along with the methods to implement them, are outlined in Table 1, with detailed elaborations provided in the corresponding sections.

Table 1. The proposed functions and methods for the identified gaps

Gaps	***Functions***	***Methods***
Limited Data Availability	Data augmentation	Adding noise
Challenges in Model Interpretability	Model interpretation	Feature importance
Difficulties in Cross-Study Comparisons	Evaluation metrics	F1 score
Lack Assessment in Generalization Capability	Cross Validation	Leave-one-out cross validation

- **Data collection**

Data collection involved placing ten participants in the front occupant seat of two vehicles: a combustion vehicle (CV) and an electric vehicle (EV). Both objective measurements and subjective assessments were collected across eight scenarios, including accelerating from stationary to 50 km/h and from 50 km/h to 100 km/h, constant highway driving at 120 km/h and 60 km/h, traversing speed bumps and bridge joints, driving on country roads, and navigating rough terrain. Detailed vehicle specifications, driving scenarios and participant demographics are listed in Tables 2 and 3 of a prior study (Wang et al., 2023a). Participants' sensitivity to auditory stimuli was also assessed. Before testing, they completed questionnaires on their sensation sensitivity, with responses summarized in Table 2 in paper E.

Vibrations were recorded from various points: the seat rail (aseat,x, aseat,y, aseat,z), armrest (aarm,y, aarm,z), and four top mounts (afront-left,z, afront-right,z, arear-left,z, arear-right,z), corresponding to longitudinal (x), lateral (y), and vertical (z) directions. The vehicle's pitch, roll, yaw, and velocities were measured at the center of gravity. Instantaneous sound was recorded at ear level due to its known effect on vibration perception (Wang et al., 2020b). Sensor locations could be found in Figure 2 of a previous study (Wang et al., 2023a).

Following each scenario, participants used questionnaires to provide subjective evaluations of vibration annoyance, as detailed in Table 3 in paper E. The evaluation results are found in Figure 4 of a previous study (Wang et al., 2023a).

- **Data augmentation**

After data collection, a dataset comprising 160 data points was gathered, including two vehicles, ten participants, and eight driving scenarios. This dataset size is insufficient for robust machine learning tasks. To address this limitation, the framework employed noise injection for data augmentation (Maharana et al., 2022). By adding random or controlled noise, this technique simulates slight environmental variations or differing conditions. The assumption driving this approach is that, under consistent conditions (same road, driver, speed, and minimal external interference), vibrations and sounds exhibit minor variations. Thus, it was expected that participants would rate their experiences similarly, justifying this method's use for data augmentation.

The recorded vibrations and sounds within the same vehicle and scenario showed consistent characteristics across participants, with slight variations reflecting inherent data variability (Wang et al., 2023a). These natural variations can be leveraged to generate new data points that maintain the core attributes of the vehicle's dynamics while introducing realistic diversity.

Thus, the original dataset was augmented by combining participants' demographic data with objective measurements from others in the same scenarios and vehicles. As shown in Figure 4 of paper E, objective measurements include: driving velocity, sound pressure, seat rail vibrations, armrest vibrations, top mount vibrations, and ride motions. Demographic and sensation sensitivity data were considered as a separate data group. For each vehicle-scenario-participant pair, a participant's personal data was integrated with randomly selected objective measurements from others in the same vehicle scenario, creating a new data point representing the participant's subjective judgment in that scenario. Random shuffling was not applied within each group due to the coupling of measured vibrations in different directions.

To confirm whether the original and augmented data came from the same distribution, a permutation test using high-dimensional Kolmogorov-Smirnov (KS) distance was performed. The null hypothesis stated that both datasets originated from the same distribution, while the alternative suggested they were from different distributions.

- **Feature Engineering**

Feature engineering in this study was informed by previous literatures. Table 2 presents the selected features, which include a combination of vehicle measurements, demographic data, and sensation sensitivity information.

The primary features extracted include raw accelerations, RMS accelerations, maximum transient vibration value (MTVV), vibration dose value (VDV), jerk, and statistics such as average, maximum, minimum, and standard deviation of speed, as highlighted by previous research. These acceleration metrics were analyzed within the 0–100 Hz range to capture significant vibrations affecting key areas like top mounts, seat rails, and armrests. Additionally, A-weighted sound pressure levels were considered in the 0–10 kHz range due to their impact on human vibration perception (Wang et al. 2020).

Demographic data, including age, gender, height, weight, and body mass index (BMI), were also considered, consistent with previous studies. Participants' occupations (experts or ordinary users) were included due to their potential influence on perception (Wang et al., 2020b). Furthermore, data on sensation sensitivity, reflecting individuals' responses to various sensory stimuli, were integrated to provide a deeper understanding of physiological and perceptual responses to environmental factors such as vibrations and vehicle dynamics.

Table 2. The extracted features

	Features
Objective measurements	• Raw accelerations; • RMS accelerations; • Maximum transient vibration value (MTVV); • Vibration dose value (VDV); • Jerk inferred from raw acceleration (e.g., $C_{seat,x}$ and C_{pitch}); • Average of driving speed; • Max and min value of driving speed; • Standard deviation of driving speed; • A-weighted sound pressures level;
Personal data	• Age; • Gender; • Height; • Weight; • BMI (Body Mass Index); • Sensation sensitivity; • Occupation (i.e., expert or general user)

- **Model Architecture**

In the proposed framework, vibration annoyance prediction was treated as a classification problem, as opposed to a regression problem, due to several advantages that enhance both the model's accuracy and its practical application. Firstly, classification enables the clear definition of vibration annoyance levels as discrete categories used in semantic scales or Likert scales. Such clarity is often lacking in regression models, which produce continuous values that require additional thresholding to become actionable. For instance, it will be tricky to decide that a prediction of 2.5 should be rounded to 2 or 3. Additionally, classification models, unlike regression models, can prevent producing meaningless predictions far beyond the scales. Moreover, classification helps in effectively managing overfitting.

Tree-based methods such as GBM and RF were employed in the proposed framework because they offer significant improvements in accuracy and robustness. ANN was also utilized in this study to facilitate comparisons both within the study and across different studies of ride experiences caused by vibrations.

- **Testing and Evaluation**

1) Evaluation metrics

The proposed framework recommends using the F1 score for its suitability in classification tasks that predict discrete categorical outcomes. It is especially beneficial for imbalanced datasets with uneven class distributions, offering a stable and reliable metric when others might be misleading (Yuxue et al., 2022). In this study, subjective comfort scores range from 1 to 5, making it a multiclass classification problem. To thoroughly assess model performance across all classes, we selected the macro F1 score. This metric calculates the F1 score for each class individually and averages them, ensuring equal weight for each class regardless of size. This approach prevents performance skewing by any particular class, making it ideal for multiclass tasks with imbalanced datasets.

$$Macro\ F_1 = \frac{1}{N}\sum_{1}^{N} F_{1,n} \qquad \text{Eq.1,}$$

where n represents the index of the class; N denotes the total number of classes.

2) Evaluation of model performance and generalization capability

This study employed the leave-one-out cross-validation method to evaluate model generalization capability, as shown in Figure 9. Each participant's measurement data from a specific vehicle and scenario was individually selected as a testing data point, while the remaining data underwent data augmentation. Within the augmented dataset, 20% was used for validation to determine the end of training and prevent overfitting, while 80% was used for training. This 80/20 split is a common strategy to balance data for training and validation (Bishop and Nasser M. Nasrabadi, 2002). Using 80% for training provides ample data to capture complex patterns, while 20% for validation reliably estimates model performance, aiding in hyperparameter tuning and detecting overfitting.

After training in each iteration, the model was tested with the designated data point. Following all iterations, predictions were collected for all data points to calculate the final performance metric. This methodical approach provided an assessment of model generalization across various scenarios and participants, enhancing the study’s reliability.

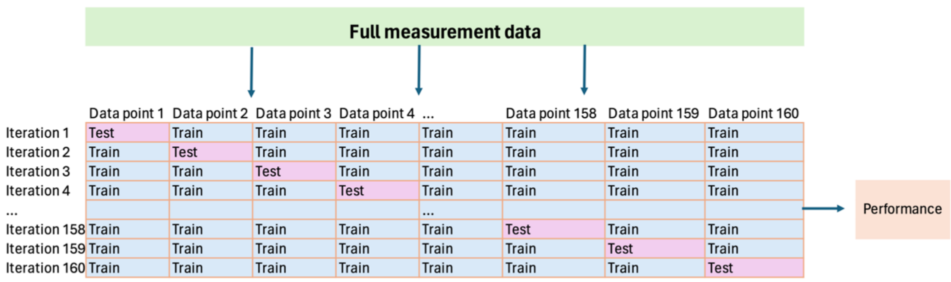

Figure 9. The process of leave-one-out cross-validation

- **Model interpretation**

The framework incorporates tree-based models, such as GBM and RF, valued for their robustness, interpretability, and capacity to manage high-dimensional data. These models provide clear insights into feature importance, effectively addressing the "black box" issue often associated with neural networks. By integrating feature importance directly into the model-building process, the framework allows for straightforward interpretation of influential features.

Additionally, the proposed framework standardizes methodologies for data augmentation, model evaluation, and model interpretation. This consistency ensures more reliable cross-study comparisons, enabling researchers to validate findings and apply them effectively across broader contexts.

Part II: Focus group

A focus group study was chosen for this research to leverage the strengths of both qualitative and interactive methods, enabling the collection of detailed feedback from a diverse group of participants (Billson, 1989). This approach fosters dynamic discussions where participants share experiences, insights, and debate the framework's strengths and weaknesses. Feedback was documented through video recordings and transcribed for content, thematic, and comparative analysis.

The study aimed to evaluate the framework's efficacy and methodologies. Discussions focused on the augmentation method, model architecture, and evaluation techniques, highlighting their strengths and limitations. The focus group also explored challenges in applying machine learning to vibration annoyance studies and considered alternative approaches and advanced techniques.

Two focus group discussions were conducted with six data science researchers—three from the automotive industry and three from other fields. Participants were introduced to the study's purpose and structure, covering the framework's components, including the augmentation method, model architecture, feature extraction, and evaluation, along with potential improvements. This introduction lasted about 30 minutes.

Participants then engaged in an open discussion based on specific and wrap-up questions outlined in Table 5 of paper E. These questions were developed from literature reviews and expert consultations to ensure relevance and provoke insightful discussions. The discussion flowed logically from specific framework elements to broader perceptions, building a further understanding before reaching general conclusions.

Participants shared opinions, experiences, and suggestions on the methodology's effectiveness, limitations, and potential improvements. During this phase, comparisons and common themes were identified across groups. The session concluded with a summary of key insights and recommendations, lasting about an hour.

The feedback underwent content analysis to identify prominent themes and keywords. Thematic analysis followed, systematically coding data based on these themes, covering method strengths and limitations and potential challenges in applying machine learning to vibration studies. Emerging themes were explored beyond predefined categories. Comparative analysis then examined response discrepancies and commonalities, enhancing understanding of varied viewpoints.

Chapter 4: Summary of Study Results

This chapter synthesizes findings from field studies, interviews, and machine learning frameworks to enhance ride comfort analysis. Field studies stressed the influences of various factors that varied across driving scenarios, while interview study highlighted the benefits and limitations of driving simulators. The machine learning framework evaluation showcased the efficacy of data augmentation and preprocessing for improved prediction accuracy and comfort factor identification, with attention paid to model interpretability and data ethics.

4.1 Field Study (Paper B and C)

This study investigated the factors influencing static comfort and dynamic discomfort in a CV and an EV, with attention to the distinct experiences arising from both stationary and moving conditions. In static scenarios, adequate space was found to be a significant determinant of comfort for both vehicle types. Participants noted that in the CV, insufficient leg room and upper body space hindered relaxation. In the EV, factors such as ample room, easy seat adjustment, and good body support were crucial for static comfort, although issues were identified with the backrest due to a wide bolster at chest level. These findings emphasize the importance of ergonomic design in enhancing passenger comfort in stationary conditions.

Dynamic discomfort presented different challenges in the two vehicle types. In the CV, discomfort was largely attributed to insufficient support, difficulty in maintaining a relaxed posture, and the impact of vibrations and noise during motion. Participants reported increased body movement and discomfort due to these dynamic elements. For the EV, sound annoyance was a predominant source of discomfort, exacerbated by a lack of body support that contributed to upper body movement. Participants experienced mismatches between sound and vibration, which were particularly disturbing. These results suggest that while the design of support structures is vital in both vehicle types, sound management is especially critical in EVs due to their distinct acoustic profiles.

The perceived annoyance from sound varied significantly between the CV and EV. In the CV, tire and wind noise were primary discomfort sources, especially at varying speeds. Participants identified tire noise, with its loudness and low frequencies, and the sharpness and fluctuation strength of wind noise, as significant irritants. In contrast, in the EV the participants reported sound annoyance primarily due to high-frequency tonal sounds from electrical components. Notably, the sound perceptions also changed with speed variations; for instance, at lower speeds, sound pressure was more negatively perceived in the EV, whereas masking effects at higher speeds improved the given judgements. These findings highlight the importance of addressing speed-related acoustic changes in designing vehicle noise mitigation strategies.

Vibration discomfort exhibited distinct patterns linked to vehicle type and motion scenarios. In the CV, low-frequency oscillations and inconsistencies between sound and vibration were key discomfort contributors, particularly during braking and over bridge joints. Few participants utilized armrests, but those who did experience discomfort from vibrations transmitted through these support points. Conversely, in the EV, discomfort was associated with movement-induced body motion.

Lastly, factors related to seat design significantly influenced comfort perceptions under both static and dynamic conditions. Seat dimensions, particularly length and contour, were frequently cited as inadequate, affecting overall ride comfort. In static conditions, participants linked comfort to seat stiffness and pressure distribution, while in motion, issues like lateral and lower body support became more prominent. Although factors such as seatbelts and temperature were evaluated, they did not emerge as primary discomfort elements in this study, potentially due to occupant familiarity and controlled testing conditions. Collectively, these insights underscore the multifaceted nature of ride comfort, necessitating a design approach that considers spatial, acoustic, dynamic, and ergonomic elements.

4.2 Interview Study (Paper D)

The adoption of driving simulators in research presents a range of advantages, particularly in the areas of safety and methodological consistency. As detailed in Paper D, simulators allow researchers to probe challenging and potentially hazardous driving scenarios in a secure environment, which would be impractical to test using real vehicles. This safety advantage is coupled with the high repeatability of experiments, enabling consistent conditions that facilitate comparative studies across diverse demographic groups and vehicle design parameters. Furthermore, the controllability granted by simulators permits the systematic creation of specific driving scenarios, allowing for precise testing and increased research efficiency by enabling rapid transitions between different road profiles and vehicle models.

Despite these advantages, driving simulators also bear significant limitations that must be considered in their application to research. As highlighted in Paper D, technicians report that space constraints and reduced motion realism impede the ability of simulators to authentically replicate real-world driving experiences, such as acceleration, deceleration, and sharp turns. These constraints potentially diminish the immersive quality of simulations and thereby compromise their validity. Hardware limitations also restrict the variety of scenarios that can be effectively simulated, necessitating careful experiment design and robust communication between researchers and technicians. Although simulators might ultimately reduce the overall research time for complex studies, the initial preparation of new scenarios can be demanding and time intensive.

The viability of using driving simulators is contingent upon the nature of the study design. Simulators are particularly effective for investigations focused on relative values, such as those exploring human-machine interactions, road safety, and driver behavior, in addition to component and design optimization. However, their application is less suitable for studies involving prolonged acceleration, extended lateral maneuvers, or scenarios requiring high ecological validity, such as dark driving conditions or snowy terrains. The potential lack of ecological validity may affect participant behavior and limit the generalizability of findings to real-world settings.

In the specific context of ride comfort studies, there are additional considerations related to the use of simulators. The study elucidates the critical role of a simulator's ability to accurately reproduce vibrations, which is essential for evaluating human response and designing effective experiments. Motion realism is a significant concern, as simulators often necessitate motion scaling to match real vehicle dynamics. This scaling is subjectively assessed and can vary among technicians, affecting study reliability. Additionally, simulators may fail to fully engage all sensory aspects of real driving, raising challenges in translating findings to actual driving conditions. The risk of simulator-induced motion sickness is another factor, with discrepancies in perception and motion potentially leading to adverse participant reactions. Some strategies include adjusting temperature and lighting conditions to reduce this risk, though their effectiveness can vary among individuals.

4.3 Framework and Focus Group Study (Paper E)

The study presents a machine learning framework designed to evaluate ride comfort, encompassing stages from data collection to model evaluation and feature importance analysis. The proposed framework integrates both subjective and objective data, offering an approach to understanding ride comfort. This methodology begins with extensive data collection, capturing subjective experiences via questionnaires and objective metrics through sensor data. Preprocessing ensures compatibility between these data types by encoding subjective judgments into numerical values and organizing data into training and testing sets. This structured approach facilitates the subsequent machine learning processes, enabling a rigorous analysis of ride comfort factors.

Model selection within the framework considers the study's purpose, ensuring appropriate algorithm choices for effective analysis. Training and validating models through cross-validation techniques minimizes overfitting and enhances the ability to generalize to new data, ensuring robustness in predicting ride comfort. Model performance evaluation, primarily using F1 scores, verifies effectiveness, with an iterative review of results aiding in refining model accuracy. The framework also incorporates feature importance analysis, using models like Gradient Boosting Machine (GBM) and Random Forest (RF) to identify key contributors to vibration discomfort in driving scenarios, thus informing potential design improvements.

The framework's application demonstrated significant enhancements in predictive capabilities when augmented data were used. These data, produced through thoughtful augmentation techniques, localized closely to original datasets, confirming their representativeness. Augmented data consistently outperformed original datasets in model evaluations, particularly with GBM and RF models, indicating stronger predictive power and better handling of diverse driving scenarios. While original datasets exhibited limited performance, especially for lower subjective ratings, augmented data extended model reliability across all categories, emphasizing the efficacy of the augmentation approach in strengthening dataset quality and model performance.

Feedback on the machine learning models within this study highlights challenges associated with data quality and the balance between complexity and interpretability. Ensuring model interpretability is crucial, particularly in practical applications like ride comfort studies. Despite the power of complex models such as Artificial Neural Networks (ANN), more straightforward models like GBM proved more consistent and user-friendly, effectively managing large datasets and capturing influential ride comfort features. Proper feature engineering and maintaining data quality through rigorous preprocessing and normalization are essential components in ensuring reliable model performance and generalization to real-world conditions.

The study also addresses ethical considerations and the importance of ensuring data representativeness and model fairness. Ethical concerns regarding data privacy and potential biases in machine learning models highlight the need for vigilance in handling sensitive occupant data and ensuring equitable model performance across diverse demographic groups. Regular audits and fairness assessments are recommended to prevent unintended bias and ensure trust in machine learning applications. The effective incorporation of varied driving scenarios and rigorous validation techniques are emphasized as critical factors for the success and applicability of machine learning in ride comfort studies, ultimately contributing to improved vehicle designs and enhanced occupant experiences.

Chapter 5: Analysis

This chapter provides an aggregated analysis of the findings from the studies to address the research questions.

5.1 RQ1: What is the definition of ride comfort from occupants' perspective?

To address RQ1, a combination of literature review and field studies was utilized to pinpoint factors that influence ride comfort specifically from the occupants' perspective.

Literature Study on Ride Comfort Factors

The literature study explored a range of factors influencing occupants' perceptions of ride comfort. Key elements identified include vibration, ride motion, sound, seat and seatbelt systems. Each factor contributes uniquely to the overall comfort experience, interacting in complex ways with the vehicle and the environment. This multivariate nature of ride comfort underscores the need for a holistic understanding of how these elements collectively influence occupant perceptions.

Further, the study revealed that occupants are exposed to multiple simultaneous inputs from the vehicle that vary depending on driving conditions. This variability highlights the dynamic context in which ride comfort is experienced, suggesting that ride comfort cannot be assessed solely based on isolated factors. Instead, understanding ride comfort requires considering how vibrations, noise levels, and movements interact under different conditions, such as varying speeds and road profiles.

Another finding from the review is that many research studies focus on identifying aspects that cause "ride discomfort" even when the term "ride comfort" is used. This discrepancy suggests a gap in understanding and defining positive comfort experiences. Therefore, identifying specific factors that are associated with perceived ride comfort in stationary conditions is one important aspect for advancing research in this area.

By synthesizing insights from existing literature, the study laid a foundation for understanding how occupants perceive ride comfort and discomfort, as well as provided a basis for the subsequent field study. This exploration of literature highlights the importance of dissecting ride comfort into its constituent elements to foster better design practices in the automotive industry.

Field Study Insights on Ride Comfort

The field study provided practical insights by obtaining direct feedback from occupants about their ride comfort experiences. This aspect of the research was crucial in offering a real-world perspective that complemented the theoretical framework established by the literature review. It became apparent from the gathered data that overall ride comfort encompasses primarily two components: initial comfort and dynamic comfort.

Initial comfort was consistently found to be influenced by factors such as ingress, the amount of available body room, seat adjustability, and support. These elements collectively contribute to the immediate sense of ease that occupants experience upon entering and settling into the vehicle. Both vehicles studied, the CV and the EV, demonstrated a shared emphasis on these factors.

Dynamic comfort presented more variation between the two vehicles. For the CV, dynamic discomfort largely stemmed from induced body movements, noticeable local vibrations, and intrusive sounds. The interplay between these physical and auditory factors influences comfort levels during motion. Conversely, in the EV, the main source of dynamic discomfort was found to be annoying sounds. The absence of traditional engine noise in EVs means that other sounds become more perceptible, leading to increased occupant sensitivity to high-frequency noises.

5.2 RQ 2: How is ride comfort influenced by sound and vibration?

The field study underscores the significant impact of sound and vibration on ride comfort, particularly regarding dynamic discomfort, in both the CV and EV analyzed.

In the CV, discomfort related to sound was primarily attributed to tire and wind noise. The loudness and low-frequency characteristics of tire noise, combined with the sharpness and fluctuation strength of wind noise, emerged as major causes from dynamic discomfort. These noises became more prominent as they contributed to an overall decrease in ride quality. Conversely, the acoustic challenges in the EV stemmed from high-frequency tonal sounds produced by electrical components. Participants reported these sounds as particularly annoying at lower speeds, where they were more negatively perceived. However, the study indicates that at higher speeds, masking effects may reduce the perceived discomfort.

Vibration was identified as another crucial factor affecting dynamic discomfort, with distinct patterns observed in the CV and EV. In the CV, discomfort was linked to low-frequency oscillations and inconsistencies between sound and vibration, especially noticeable when traversing bridge joints. The lack of adequate body support further exacerbated these issues, challenging passengers to maintain a relaxed posture and resulting in increased body movement. Similarly, in the EV, discomfort due to vibration was closely associated with movement-induced body motion. The findings indicated that insufficient ergonomic support resulted in significant upper body movement, intensifying the discomfort experienced by passengers.

The study particularly emphasizes the need to consider both immediate and long-term responses to sound and vibration in assessment methodologies. One of the findings is the differentiation between immediate reactions and overall perceptions of ride comfort. Participants noted that sound and vibration affected their ability to relax, even when these elements were not rated as immediately annoying. This indicates a complex relationship where immediate assessments do not fully capture the long-term impact on ride comfort.

When it comes to the characterization of vibration discomfort, the study found participants struggled to articulate specific vibration characteristics directly. As a result, the researchers turned to observable indicators such as body movement and the relative motion between body parts to assess vibration discomfort. Low-frequency vibrations were identified as one important contributor to discomfort, often leading to noticeable body movements and subtle resonance effects. These indirect indicators provide an approach for understanding and mitigating vibration-related discomfort.

5.3 RQ 3: How could advanced technology be utilized in ride comfort, specifically vibration discomfort prediction and assessment?

To maximize the use of advanced technologies such as driving simulators and machine learning in ride comfort, specifically vibration discomfort assessment, it is essential to establish a framework that integrates each component effectively.

Incorporating Advanced Technology: Initial Considerations

Achieving enhanced ride comfort, particularly in relation to reducing vibration discomfort, calls for a strategic integration of advanced technologies such as driving simulators and machine learning. This integration is important for potentially transforming the framework of ride comfort evaluation and vehicle design. To effectively utilize these technologies, certain initial considerations should be addressed to ensure a cohesive and comprehensive approach.

Driving simulators provide a safe and controlled testing environment with the unique advantage of rapidly switching between various vehicle designs and driving scenarios. This flexibility allows researchers to collect instantaneous responses to a number of conditions/designs and make comparison across them. Meanwhile, machine learning approaches offer the ability to identify patterns and predict outcomes related to vibration discomfort. These approaches could process complex datasets from both field and simulator studies, revealing insights that might not be immediately evident through traditional analysis.

Utilizing Driving Simulators

The use of driving simulators begins with defining clear study objectives and test scenarios. This helps direct methodological and technological choices, ultimately providing actionable insights. Simulators could be configured to enhance realism by employing motion-cueing systems and advanced algorithms that simulate realistic auditory and tactile response dynamics. In structured testing, test plans are developed to cover driving scenarios of interest. Sensors collect detailed data, such as sound, vibration, and ride motions, enabling analysis of the interplay between stimuli and their impact on the dynamic discomfort. The analysis phase evaluates collected data to discern patterns and correlations.

Leveraging Machine Learning

The initial phase of leveraging machine learning in dynamic discomfort assessment involves data collection and augmentation. This includes gathering datasets from both field and simulation studies focusing on vibrations and sounds. Augmentation techniques are employed to enhance dataset robustness, ensuring the development of accurate and generalizable machine learning models. The model development phase includes selecting and training predictive models to predict dynamic discomfort. Feature importance analysis could provide further insights regarding the contribution of various factor on experienced vibration discomfort.

Creation of a Feedback Loop for Continuous Improvement

The establishment of a feedback loop is an essential strategic advantage in integrating advanced technologies. This feedback loop is characterized by an iterative cycle of data collection, prediction and validation that spans both simulated environments and real-world applications. By employing this continuous cycle, vehicle systems can be continuously refined, aligning more closely with both technological advancements and evolving consumer needs.

Data collected from real-world driving conditions or during simulations is analyzed to identify vibration discomfort issues. Predictions on occupant experiences could be made based on the collected data. Validation involves comparing predictions with real-world data to verify the accuracy and reliability of the predictions, where insights gained from this comparison are fed back into the system, guiding further refinements and establishing a cycle of continuous improvement.

This process transforms vibration discomfort assessment from a static goal into a fluid, adaptable quality. Instead of being viewed as a fixed element to be checked off a list, vibration discomfort becomes an ongoing pursuit, constantly adapting to new data, technological innovations, and user responses.

5.4 Comparative Analysis

Methodology and Setup

Field studies involve collecting data directly from occupants as they experience actual driving conditions, providing genuine observations of experienced ride comfort and the effects of various factors such as sound and vibration. However, field studies have limitations such as limited control over external variables, time consumption, and extensive resource dependance. Researchers have difficulties ensuring the consistency and repeatability of the results, but despite these challenges, field studies remain valuable for understanding how occupants perceive the overall ride comfort as well as the sounds and vibrations, offering insights that are grounded in real-world experiences.

Driving simulators offer a distinct advantage by providing a controlled and repeatable environment for testing ride comfort. Unlike field studies, simulators allow researchers to manipulate specific conditions regardless of physical restrictions in the real world, enabling precise adjustments to scenarios such as speed, road type, and environmental factors. Additionally, the capability of rapid switching across various vehicle designs afforded by driving simulators ensures that test subjects can evaluate their experiences by instantaneous perception, improving the accuracy and efficiency of comparison. However, simulators may lack the full ecological validity of real-world studies, as they might not mimic the complete range of sensory experiences encountered on the road.

Machine learning methodologies leverage real-world datasets to identify patterns and predict outcomes related to ride comfort. These approaches involve training models to capture complex relationships between variables such as vibration, sound, and occupant experiences. The advantage of machine learning lies in its ability to provide insights that might not be immediately apparent through traditional analysis methods. However, the success of machine learning models depends heavily on the robustness of the data used for training. Ensuring data quality is crucial, as inaccurate or biased datasets can lead to misleading predictions. When properly implemented, machine learning offers a powerful tool for advancing predictive capabilities and informing design improvements in the automotive industry.

Data Collection and Analysis

Field studies involve collecting direct, real-time data from the real world, allowing researchers to observe occupant experienced ride comfort under genuine driving conditions. This method captures the variability in ride comfort due to factors such as road conditions and vehicle types, offering insights into how variables including sound and vibration impact occupant experiences. The primary advantage of field studies is the real-world applicability, providing context-rich data that reflect actual conditions. However, the inherent variability can also pose challenges in drawing consistent conclusions across different studies, especially when the field studies are resource intensive and time consuming.

In contrast, driving simulators gather controlled data on specific scenarios, allowing researchers to isolate and analyze the influence of particular variables on ride comfort. Utilization of driving simulators provides a possibility for detailed examination of how these variables interact under controlled conditions. This approach enables precise manipulation of variables, enhancing the reliability and consistency of the data collected. The ability to replicate scenarios with exact specifications ensures that researchers can conduct systematic analyses and identify causal relationships with greater certainty.

Machine learning approaches augment the size of collected data to detect patterns and derive insights into occupant experienced ride comfort. By analyzing extensive datasets, machine learning models can uncover complex relationships that might not be evident through traditional analysis. A critical advantage of this approach is the capability of feature importance analysis, which assesses the significance of various factors in predicting ride comfort. This analysis offers deeper insights into which variables most influence passenger experiences, guiding targeted interventions to enhance comfort. Machine learning's analytical power enables the identification of trends and provides a robust framework for predictive modeling and optimization in vehicle design.

Advantages and Limitations

Field studies offer the distinct advantage of capturing realistic observations and behaviors by conducting research in natural settings or in designed settings to mimic the real world. Such authenticity provides valuable insights into how various factors impact ride comfort in everyday scenarios. However, the very nature of field studies introduces challenges related to limited repeatability and variable control. Factors such as road conditions can introduce significant variability, making it difficult to replicate findings consistently across different studies. This lack of control can complicate efforts to draw clear, generalizable conclusions.

In contrast, driving simulators provide the benefit of safe and repeatable testing conditions. By offering a controlled environment, simulators allow researchers to precisely manipulate variables such as speed and road conditions to explore specific aspects of ride comfort. The ability to systematically experiment and replicate scenarios enhances the reliability of the collected data. Moreover, driving simulators allow researchers to efficiently switch across different test scenarios or vehicle designs, providing possibilities for instantaneous comparisons in occupant experiences. Despite these strengths, simulators face limitations, including a potential lack of motion realism and ecological validity. Although they can mimic many aspects of driving, simulators may not fully capture the complex realities of real-world driving, which can affect the applicability of findings to actual driving experiences.

Studies using machine learning methods cannot replace field studies or simulator studies; rather, it serves as a complementary tool that can effectively utilize the data derived from field studies and simulator studies. Machine learning approaches process extensive datasets to detect intricate patterns and predict ride comfort outcomes with high precision. Their ability to adapt and refine predictions over time, as new data becomes available, supports continuous improvement in model performance. However, machine learning approaches are heavily dependent on the quality of the training data. Poor-quality or biased datasets can lead to inaccurate or misleading predictions, underscoring the importance of ensuring robust, representative data. This dependency highlights a critical challenge that must be addressed to achieve reliable outcomes and maximize the potential of machine learning in enhancing ride comfort assessments.

Application and Integration

Field studies play a crucial role in informing real-world applications by providing immediate feedback based on authentic occupant experiences. The insights gained from such studies are directly applicable to real-world contexts, helping researchers understand how different factors affect ride comfort in actual driving conditions.

Driving simulators, by contrast, support iterative testing and real-time scenario analysis. Their controlled environment allows for the systematic exploration of various driving conditions, enabling researchers to experiment with different variables and assess their impact on ride comfort.

Machine learning further enhances this process by boosting predictive capabilities and enabling real-time adjustments within vehicle systems. By processing large datasets, machine learning models can predict discomfort and suggest adjustments dynamically, leading to more responsive and tailored vehicle designs.

Field studies, driving simulators, and machine learning methodologies each offer unique contributions and encounter challenges in investigating ride comfort, yet they complement and support each other in meaningful ways. Field studies provide real-world insights, although they face challenges related to control and consistency. Driving simulators, on the other hand, offer controlled settings that mitigate these challenges. While simulators may lack complete ecological validity, they fill the gaps inherent in field studies by providing a repeatable platform for controlled experimentation. Machine learning further augments these methods by analyzing data from both field studies and simulators to uncover patterns and predict outcomes related to ride comfort. By leveraging robust datasets, machine learning models enhance understanding and prediction, offering insights not readily apparent through traditional analysis.

Chapter 6: Proposed guidelines

6.1 Guidelines for field study on ride comfort

The guidelines for conducting a field study on ride comfort in passenger cars were developed through a review and synthesis of existing literature and empirical insights gained from field studies. The process aimed to establish a structured and reproducible framework that allows researchers to effectively evaluate the experienced ride comfort and to investigate the impact of sound and vibration on ride comfort.

Table 3 outlines the field study design for investigating ride comfort in passenger cars, focusing on the impact of sound and vibration. It addresses objectives, vehicle selection, participant recruitment, data collection, ethical considerations, study procedures, data analysis, and result evaluation.

Table 3. Guidelines for field study on ride comfort.

Study Design and Planning	Define Objectives: • Clearly outline the objectives of the field study. • Identify specific research questions, such as understanding the impact of sound and vibration on occupant comfort or comparing the ride comfort of different vehicle types. Select Vehicle Types and Scenarios: • Choose the vehicle(s) to investigate the characteristics of interest. • Design representative driving scenarios that could capture the specific sounds and vibrations pertinent to the study's objectives
Participant Selection and Preparation	Recruit Representative Participants: • Ensure the selected group of participants can cover the demographics (age, gender, driving experience) of expected the customer group to capture the range of comfort perceptions. Participant Briefing: • Provide detailed instructions and brief participants on the study protocol. • Familiarize participants with any equipment they will use during the study, such as in-car sensors and questionnaires.
Data Collection	Subjective Measurements: • Use questionnaires to collect subjective data on occupants' experiences. Include questions about perceived vibration and noise discomfort and overall ride comfort judgement. • Collect additional contextual information, such as participants' seating positions and postures during the ride. Objective Measurements: • Install sensors in the vehicle to capture objective data such as vibration (e.g., vibrations on seat rail and armrest), sound levels representative for the participants experience, and ride motion (e.g., pitch, roll, yaw). • Collect additional vehicle performance data, including speed, road conditions, and driving behavior.
Ensuring Data Quality	Pilot Testing: • Conduct pilot tests to validate data collection methodologies and refine study procedures. • Address any issues with data collection tools or protocols identified during pilot testing.
Ethical Considerations	Privacy and Confidentiality: • Ensure that all collected data are handled with strict confidentiality. • Use anonymization techniques to protect participant identities and comply with data protection regulations. Informed Consent:

	• Clearly explain the purpose of the study, its procedures, and any potential risks to participants. • Obtain written informed consent from participants before involving them in the study.
Conducting the Study	Standardized Procedures: • Implement standardized driving routes and protocols for consistency across different vehicles and scenarios. • Ensure that driving conditions are as controlled as possible (e.g., weather, traffic) to avoid introducing variability that could affect the results. Data Logging and Monitoring: • Continually log and monitor incoming data during field studies. Address any equipment malfunctions or inconsistencies immediately. • Ensure that participants are comfortable and safe throughout the study and provide them with breaks as needed.
Data Analysis	Data Preprocessing: • Perform initial data checks to identify and correct any errors or inconsistencies in the data. • Convert subjective ratings to numerical values for compatibility with statistical and machine learning analyses. Combining Subjective and Objective Data: • Integrate subjective and objective data into a unified dataset for analysis. • Use statistical methods or machine learning models to identify patterns and correlations between different types of data.
Evaluating Results	Identify Key Factors: • Analyze data to identify the key factors affecting ride comfort, such as specific vibration frequencies, noise levels, or vehicle motions. • Interpret the significance of identified factors in relation to participant comments and feedback collected during the study. Model Validation: • Validate findings using cross-validation or similar techniques to ensure that identified patterns are robust and generalizable. • Report both statistically significant and practically relevant findings to provide a balanced view of ride comfort factors.

6.2 Guidelines for using driving simulators in ride comfort studies

The findings from literature and the interview study are merged into guidelines on how to conduct user studies, particularly focusing on user experience and ride comfort in high-level driving simulators (Table 4). These guidelines aim to help researchers use driving simulators in user studies, while they also address potential limitations and carefully design studies regarding validity.

Table 4. Guidelines for using driving simulators in ride comfort studies

General advantages of using simulators	*Encourage researchers to apply the advantages:* • Safety • Repeatability • Reduced practical constraints • Controllability • Efficiency
General limitations of using simulators	Encourage researchers to weigh these factors: • Space limitations • Restricted motion realism • Hardware dependence • Communication difficulties between researchers and technicians • Time consuming for new scenario development
Types of studies suggested in simulators	Encourage the use of simulators for experiments requiring: • Reduced risk

	• Controlled environments • Precise manipulation of variables • Rapid transitions between study objects
Types of studies not suggested in simulators	Caution against using simulators for studies involving: • Acceleration and deceleration • Extensive lateral maneuvers • Low-light conditions • Icy surfaces • Estimation of inter-vehicle distances Discourage the use of simulators for absolute value studies that directly compare with real-world measurements
Design of simulator studies	Ethical Considerations: • Ensure participant safety and well-being throughout the experimental procedures. Task Duration: • Consider the duration of simulation sessions and potential effects on participant experience and behavior. • Implement breaks or rest periods to mitigate the impact of prolonged simulation exposure. Data collection: • Consider the methods for collecting subjective judgements before, during and after the test scenarios (e.g., interviews, questionnaires, estimation scales and instant judgements). • Consider adding objective data collection during the simulation if useful for the study (e.g., vibrations, noise and ride motion of the vehicle).
Setup of simulators	Resource Allocation: • Allocate resources to support the design, implementation, and analysis of the simulation study. • Select appropriate driving scenarios tailored to the capabilities and limitations of the simulator. • Ensure that control conditions are designed and implemented to isolate specific variables of interest. Simulation Fidelity: • Assess the fidelity of the simulator in replicating real-world driving dynamics. • Minimize biases and ensure the fidelity of the simulation environment. • Consider the trade-offs between simulator realism and practical constraints. Environmental Factors: • Control environmental factors such as lighting and temperature within the simulation environment. • Consider how environmental factors may influence participant behavior and responses.
Specific guidelines for user performance	• Encourage the use of simulators for dynamic scenarios that require real-time decision-making by participants. • Caution against scenarios that may not accurately capture real-world driving experiences, such as low-light conditions.
Specific guidelines for user experience	• Prioritize the investigation of ergonomic factors, HMI systems, ambient conditions, and the perception variation under various conditions. • Acknowledge limitations in simulating real-world factors like ingress and legroom.
Specific guidelines for user ride comfort	Assess various driving scenarios: • Recommend assessing various driving scenarios (e.g., bumpy roads) to study ride comfort. • Acknowledge challenges in replicating real-world sensations like acceleration and deceleration in simulators. Prioritize relative value studies:

• Emphasize relative value studies over absolute value studies to account for differences in simulation conditions and scaled motions. • Encourage detailed analysis of changes or differences within the simulated environment. Minimize impact of virtual environment: • Mitigate biases caused by simulator fidelity, motion cues, and visual displays to ensure the validity and reliability of results. • Consider potential impacts on participant behavior and responses, such as reduced risk perception and simulator-induced discomfort.

6.3 Guidelines for using machine learning in ride comfort studies

Table 5 summarizes the framework design and planning for a ride comfort study focusing on machine learning applications. It includes defining objectives and appropriate metrics, data collection and preprocessing, model selection and training, performance evaluation and interpretation, implementation and validation, ethical considerations, maintaining model performance, and leveraging advanced techniques. Each section outlines essential steps and considerations to ensure robust, accurate, and ethical analysis aimed at predicting ride comfort.

Table 5. Guidelines for using machine learning in ride comfort studies

Framework Design and Planning	Define Objectives • Clearly outline the objectives of the study. • Identify specific research questions and the intended objectives. Select Appropriate Metrics • Choose relevant performance metrics like F1 scores for classification tasks or MAE/RMSE for regression tasks. • Consider metrics that align with your research objectives and can effectively evaluate model performance.
Data Collection and Preprocessing	Data Collection • Gather a diverse dataset from participants that adequately represent the potential user population. • Collect both subjective measurements (e.g., user comfort ratings via questionnaires) and objective measurements (e.g., vibration, sound, and motion data from a field study or simulator study). Data Preprocessing • Convert subjective judgments and demographic data into numerical values to ensure compatibility with machine learning processes. • Divide the data into appropriate subsets, such as training and testing sets, ensuring that testing data remains unseen during training. Data Augmentation • Employ data augmentation techniques to enhance dataset size and diversity while preserving data integrity. • Validate augmented data to ensure it remains representative of actual ride comfort scenarios.
Model Selection and Training	Choose Suitable Models • Select machine learning models based on study objectives and dataset characteristics. Consider models like Gradient Boosting Machine (GBM), Random Forest (RF), and Artificial Neural Networks (ANN). • Evaluate the suitability of each model for your specific use case, considering factors like interpretability and computational complexity. Training and Validation • Train models using cross-validation techniques to prevent overfitting and ensure generalizability. • Split the dataset into training and testing subsets, keeping the testing set separate during training for unbiased evaluation.
Model Evaluation and Interpretation	Performance Evaluation

	• Assess model performance using the selected metrics. For classification tasks, compute F1 scores and macro F1 scores to evaluate predictive efficacy across all categories. • For regression tasks, incorporate metrics like MAE, RMSE, and MSE to understand prediction errors. Feature Importance Analysis • Analyze feature importance to identify key factors influencing ride comfort. For GBM and RF models, calculate feature importance based on the reduction in the loss function during training. For ANN models, aggregate attention weights across decision steps and samples to derive global importance scores. • Use the insights from feature importance to inform design improvements and enhance occupant comfort.
Implementing and Validating Models	Robust Validation • Use robust validation techniques like leave-one-out cross-validation to assess model generalization capability. • Regularly update and revalidate models with new data to maintain accuracy and relevance. Real-Time Implementation • Integrate models into real-time systems for dynamic adjustments based on occupant feedback. • Ensure models are scalable and adaptable to new data patterns and deployment requirements.
Ethical Considerations	Privacy and Data Security • Implement robust data anonymization and security measures to protect personal data collected from participants. • Ensure compliance with data protection regulations and maintain user trust through transparent data handling practices. Bias and Fairness • Ensure data used for training are representative of diverse populations and driving scenarios to prevent discriminatory outcomes. • Conduct regular audits and fairness assessments to verify that models provide equitable predictions across different demographic groups.
Maintaining Model Performance	Continuous Updates • Regularly update and retrain models with new data to keep them current and accurate. • Monitor model performance over time and adjust as needed to address emerging trends and new use cases. Handling Data Dependencies • Address the dependency on high-quality data by ensuring comprehensive and diverse data collection processes. • Regularly reassess data quality and completeness and implement additional data augmentation techniques if necessary.
Leveraging Advanced Techniques	Exploring Alternative Augmentation Methods • Investigate techniques like the Synthetic Minority Over-sampling Technique (SMOTE), Generative Adversarial Networks (GANs), and simulation-based augmentation to improve dataset diversity and representativeness. • Evaluate the effectiveness of these methods in enhancing model performance and generalization capabilities. Employing Ensemble Methods • Use ensemble methods such as stacking or blending to combine the strengths of GBM, RF, and ANN models, thereby improving predictive capabilities and reducing biases. • Ensure that ensemble methods are implemented in a manner that maintains interpretability and transparency.

Chapter 7: Overall Discussion

The primary purpose of this study is to enhance the understanding of ride comfort by leveraging field studies, driving simulators, and machine learning approaches. By systematically investigating the influence of sound and vibration on occupant comfort, this research aims to propose guidelines for utilizing these ride comfort study approaches. The study's insights contribute to developing effective methodologies for assessing and optimizing ride comfort across various conditions and vehicle types.

7.1 Strengths and Weaknesses

The strengths of this study are notably anchored in its multidisciplinary approach, which adeptly combines technical and human-centric methodologies. With the author's expertise in applied acoustics and human factors, the research effectively integrates subjective and objective data collection methods, establishing a robust framework for evaluating ride comfort. This mixed-method approach enriches the understanding of the complex interactions between sound, vibration, and human perception, providing a comprehensive perspective on these dynamics.

Further enhancing the study is the utilization of advanced technologies, including driving simulators and machine learning methods, which facilitate rapid testing and detailed analysis across various driving scenarios. These tools significantly bolster the study's predictive capabilities and adaptability. The emphasis on feature importance within this technological framework lays a groundwork for future research and applications within the automotive industry, informing design innovations.

Despite these strengths, several methodological weaknesses have surfaced that could affect the comprehensiveness and applicability of the findings. A primary limitation is the relatively small and demographically homogenous sample size used in the field study. This limitation potentially restricts the study's ability to comprehensively capture the diverse spectrum of occupant experiences and perceptions, thereby impacting the generalizability of the results. Expanding the sample to encompass a broader range of demographic groups would likely enhance the robustness of the study's insights.

Additionally, the reliance on subjective data obtained through questionnaires and interviews poses challenges. Such data are inherently susceptible to biases and variability due to individual differences in perception, which might affect the objectivity and accuracy of the conclusions. Future studies may benefit from incorporating more objective assessments to complement subjective reporting, thereby achieving a more balanced analysis.

The focus on short-term testing conditions presents another concern, as these conditions may not effectively capture the cumulative effects of sound and vibration over extended periods. A thorough understanding of these long-term impacts is essential for a comprehensive evaluation of ride comfort, which suggests a need for studies with more extended testing protocols.

While driving simulators offer a controlled environment for testing, they present distinct challenges. These simulators often struggle to replicate the dynamic intricacies of real-world driving, potentially impacting the ecological validity of the findings. Maneuvers involving large lateral motions and acceleration are particularly difficult to accurately simulate, possibly leading to discrepancies when results are compared to real-world scenarios. This highlights the necessity for careful planning and execution in designing simulator-based studies.

Machine learning techniques, though advantageous for enhancing dataset size, model interpretation, and cross-study comparison, introduce complexity. The process of data augmentation, while expanding the data available for training, risks embedding artificial variance. This could skew model training and lead to overfitting or imprecise predictions when these models are applied to real-world conditions. Consequently, a cautious approach is required to ensure the integrity and validity of the model outcomes. Another limitation is the evaluation of the machine learning framework, which is based on limited data from a restricted field study consisting of only eight driving scenarios and ten participants. This limited dataset might not be sufficient to ensure reliable results that can be generalized to a broader population. Hence, increasing the number of participants and scenarios could strengthen the model's robustness and improve the reliability of the results.

7.2 Generalization of Study Findings

The methods and findings of the current study, encompassing field and simulator studies as well as machine learning approaches, provide a framework for advancing knowledge in the domain of ride comfort analysis. When compared with existing literature, these findings demonstrate both adherences to established knowledge and distinct advancements that contribute to the field's evolution.

The current field study's methodology and findings align closely with foundational work (Griffin and Erdreich, 1991), which examined the complex interplay between human response and mechanical vibrations. Similarly, Paddan and Griffin's (2002) evaluation of whole-body vibration in vehicles underscores the importance of real-world vibration in understanding ride comfort. These studies emphasize the importance of using empirical data, such as sound, vibration, and ride motions, to evaluate occupant experiences. The present study builds upon these foundations by expanding participant demographics and examining a range of driving scenarios, thereby offering further insights that could be generalized across various vehicular environments.

Unlike previous studies that focused on the influence of sound or vibration under a single driving scenario (Hassan and McManus, 2002; Sezgin and Arslan, 2012; Wang et al., 2020a), this study took a comparative approach by utilizing two cars to represent different car types. This allowed for an exploration of occupants' ride experiences across different conditions. While there are naturally differences between the cars used in this study and other models of CVs and EVs in terms of sound and vibration, the findings and methodology could support further research in other types of passenger cars.

This study observed that low-frequency vibrations significantly influenced occupant comfort, echoing similar results from research (Beard and Griffin, 2013; Hassan and McManus, 2002), who noted the pervasive impact of low-frequency vibrations in automotive environments. Such vibrations typically arise from engine operations, road interactions, and suspension systems, as described by (Griffin and Erdreich, 1991) in their comprehensive exploration of human responses to vehicle vibrations. Furthermore, Wang et al. (2020a) highlighted that modern vehicles equipped with automatic start/stop systems frequently expose passengers to low-frequency sound and vibration cycles, potentially affecting perceived comfort levels. These repetitive noise patterns and vibrations, common in various CV models, suggest that strategies for mitigating low-frequency disturbances, such as improved seat design and suspension tuning, could be universally beneficial. The alignment of this study's findings with these established research works supports the argument that addressing low-frequency sound and vibration is crucial for enhancing occupant ride comfort across different CVs, thereby offering a pathway for generalizing ride comfort improvements industry-wide.

The findings from the current field study can be generalized to a wider range of EVs by addressing the common challenges associated with high-frequency tonal sounds that occupants experience across different EV models. In this study, it was noted that the high-frequency sounds primarily emanating from the electric motor and were major contributors to experienced discomfort. This aligns with the work of (Govindswamy and Eisele, 2011), who found that high-frequency tonal noise is a recurrent issue in various EVs, impacting the overall acoustic environment and passenger comfort.

Aligned with the findings in (He et al., 2021), the annoying high frequency tonal sounds in EVs could be masked to improve the sound quality. The current study underscored how these high-frequency sounds could be masked by wind noise at higher speeds, reducing their perceptual impact. This suggests that leveraging aerodynamic noise could be a viable strategy in acoustic design to mitigate tonal disturbances.

Some studies (Akai et al., 2020; Bhiwapurkar et al., 2011) have assessed instantaneous perception to sound or vibration subjectively. However, this study not only judged the perception of sound and vibration instantaneously but also explored their overall influence. The research revealed a discrepancy between participants' immediate responses and their overall perception of sound in both vehicles. Difficulties in relaxing were attributed to the experienced sound, even if it was not initially rated as annoying, suggesting that short-duration tests may underestimate the true impact of sound.

During the interviews, participants seldom made direct judgments about the characteristics of vibration. Instead, they related vibration discomfort to resonance within their own body and resultant body movement. These finding parallels difficulties observed in other studies (Paddan and Griffin, 2002) where describing vibration assessments is challenging. The findings from the follow-up interviews show that induced body movement be used as a more effective indicator of vibration discomfort, thereby enhancing the evaluation of ride comfort across different studies and vehicle types.

In the realm of simulator studies, the current study affirms the enhanced safety, repeatability, and controllability provided by driving simulators (Bella, 2005). The controlled and repeatable setup ensures participant safety and enables precise manipulation of experimental variables, enhancing research reliability. The current study emphasized the benefit of isolating variables and conducting experiments with fewer practical constraints or even in optimal environments. Additionally, driving simulators could enhance efficiency by facilitating rapid transitions between various components, structures, and vehicle models. These capabilities are especially pertinent for exploring the complex interactions between human perception and vehicle mechanics, making simulators a useful tool for ride comfort research.

As highlighted in Paper E, the proposed machine learning framework offers an approach to enhancing dataset size and variability while maintaining data integrity. Compared with traditional frameworks (Cieslak et al., 2020; Du et al., 2021), which often struggle with small datasets or less interpretation capability, this framework addresses these limitations effectively. The proposed framework is more suited for providing guidelines and making general predictions in the industry, rather than studying the influence of individual occupants. Its robustness and ability to handle large datasets make it promising for identifying broader trends and informing design and operational decisions in vehicle dynamics. However, for research and applications that require precise analysis of how individual demographics influence vibration annoyance, more targeted methods and rigorous validation would be needed to maintain the accuracy and relevance of personal demographic data. Based on the comparisons across different models, it is recommended to favor GBM and RF over ANNs in scenarios with limited data availability. However, under circumstances where extensive data and computational resources are available, and where capturing complex feature interrelations is critical, ANNs, including models like TabNet, might be more appropriate. Providing explicit implementation details and the duration of training for each model could further elucidate these comparative performance outcomes.

In summary, the mixed-methods approach utilized in the current study developed an approach to evaluate and predict the experienced sound and vibration. Previous research (Griffin and Erdreich, 1991) underscores the value of an interdisciplinary approach, combining quantitative and qualitative data, which the current study has similarly adopted. Furthermore, the findings from (Griffin and Erdreich, 1991) regarding the variability of human responses to vibrations supports the importance of including demographic factors in the analysis. The current study builds on this approach by incorporating demographic data into the machine learning feature extraction process.

By synthesizing real-world insights from field studies, controlled experiments in simulators, and advanced predictive modeling, the current work not only corroborates established findings in the existing literature but also offers contributions through its methodological advancements. These efforts enhance the ability to generalize findings across varied contexts, laying a foundation for future research and practical applications in automotive and transport industries.

Chapter 8: Conclusions

The overall conclusion is that ride comfort, from the occupants' perspective, encompasses two primary components: initial comfort and dynamic discomfort. Initial comfort is influenced by factors such as ingress, available body space, seat adjustability, and support, providing an immediate sense of ease upon vehicle entry. This is consistently crucial across both the CV and the EV. Dynamic comfort, however, varies between vehicle types, with the CV primarily affected by body movement and intrusive sounds, while the EV are influenced mainly by high-frequency noises from electrical components. This dual-component framework underscores the complex interplay of multiple variables that affect passenger comfort.

Both sound and vibration are pivotal in shaping ride comfort. In the CV, tire and wind noise notably affect dynamic discomfort, with low-frequency vibrations contributing to discomfort, primarily during engine start/stop phases. The EV experience differs, with high-frequency tonal noise being the predominant source of discomfort, particularly at lower speeds due to lesser masking by wind noise. The study emphasizes evaluating both immediate and sustained reactions to sound and vibration, noting the necessity of considering both instantaneous and cumulative impacts on passenger comfort.

The integration of driving simulators and machine learning provides innovative pathways for assessing and predicting ride comfort. Driving simulators offer controlled environments to isolate variables and facilitate rapid scenario testing, despite limitations in representing large-scale motions. The proposed guidelines also emphasized the importance of environmental factors, simulation fidelity, and ethical considerations in study design. The machine learning framework addresses challenges in ride comfort assessments, specifically targeting data limitations, model interpretation, and cross-study comparisons. By combining occupant demographics and objective measurement data, leveraging data augmentation, and employing cross-validation techniques, the framework enhances prediction accuracy and insights into ride comfort factors. However, it requires careful management of training data quality and expertise to ensure models are generalizable across diverse datasets and real-world conditions.

Overall, this integrated approach reveals that multiple factors influence ride comfort, varying across vehicle types and scenarios. A single test scenario is insufficient for comprehensive assessment, prompting future research to focus on diverse factors tailored to both CV and EV. The proposed guidelines offer insights for the industry, guiding field studies, driving simulator use, and machine learning applications to enhance ride comfort assessments in automotive design.

References

Adam, S. A., & Jalil, N. A. A. (2017). "Vertical Suspension Seat Transmissibility and SEAT Values for Seated Person Exposed to Whole-body Vibration in Agricultural Tractor Preliminary Study." *Procedia Engineering*, *170*, 435–442. https://doi.org/10.1016/j.proeng.2017.03.070

Akai, A., Ichimaru, N., & Hirao, R. (2020). "Research on Subjective Rating Prediction Method for Ride Comfort with Learning." *SAE Technical Papers*, *No. 2020-01-1566*. https://doi.org/10.4271/2020-01-1566

Alayrac, M., Marquis-Favre, C., & Viollon, S. (2011). "Total annoyance from an industrial noise source with a main spectral component combined with a background noise." *The Journal of the Acoustical Society of America*, *130*(1), 189–199. https://doi.org/10.1121/1.3598452

Arnold, J. J., & Griffin, M. J. (2018). "Equivalent comfort contours for fore-and-aft, lateral, and vertical whole-body vibration in the frequency range 1.0 to 10 Hz." *Ergonomics*, *61*(11), 1545–1559. https://doi.org/10.1080/00140139.2018.1517900

Bakker, R. H., Pedersen, E., van den Berg, G. P., Stewart, R. E., Lok, W., & Bouma, J. (2012). "Impact of wind turbine sound on annoyance, self-reported sleep disturbance and psychological distress." *Science of the Total Environment*, *425*, 42–51. https://doi.org/10.1016/j.scitotenv.2012.03.005

Basri, B., & Griffin, M. J. (2012). "Equivalent comfort contours for vertical seat vibration: Effect of vibration magnitude and backrest inclination." *Ergonomics*, 55.8: 909-922. https://doi.org/10.1080/00140139.2012.678390

Beach, T. A. C., Parkinson, R. J., Stothart, J. P., & Callaghan, J. P. (2005). "Effects of prolonged sitting on the passive flexion stiffness of the in vivo lumbar spine." *The Spine Journal*, 5.2: 145-154. https://doi.org/10.1016/j.spinee.2004.07.036

Beard, G. F., & Griffin, M. J. (2013). "Discomfort caused by low-frequency lateral oscillation, roll oscillation and roll-compensated lateral oscillation." *Ergonomics*, Vol. 56, Issue 1, pp. 103–114. https://doi.org/10.1080/00140139.2012.729613

Bella, F. (2005). "Validation of a driving simulator for work zone design." *Transportation Research Record*, *1*(1937), 136–144. https://doi.org/10.3141/1937-19

Bellem, H., Klüver, M., Schrauf, M., Schöner, H. P., Hecht, H., & Krems, J. F. (2017). "Can We Study Autonomous Driving Comfort in Moving-Base Driving Simulators? A Validation Study." *Human Factors*, *59*(3), 442–456. https://doi.org/10.1177/0018720816682647

Bellem, H., Thiel, B., Schrauf, M., & Krems, J. F. (2018). "Comfort in automated driving: An analysis of preferences for different automated driving styles and their dependence on personality traits." *Transportation Research Part F: Psychology and Behaviour*, *55*, 90–100. https://doi.org/10.1016/j.trf.2018.02.036

Bellmann, M. A. (2002). "Perception of Whole-Body Vibrations: From basic experiments to effects of seat and steering-wheel vibrations on the passenger's comfort inside vehicles." *Akustik. Universitt Oldenburg*, 209.

Berge, T., & Haukland, F. (2019). "The concept of adaptive AVAS-results from a small test program." *INTER-NOISE and NOISE-CON Congress and Conference Proceedings*, *259*(9), 335–346.

Berglund, B., Preis, A., & Rankin, K. (1990). "Relationship between loudness and annoyance for ten community sounds." *Environment International*, *16*(4-6): 523-531. https://doi.org/10.1016/0160-4120(90)90021-W

Berglund, U., Lindvall, T., & Berglund, B. (1976). "Scaling loudness, noisiness, and annoyance of community noises." *Journal of the Acoustical Society of America*, *60*.5: 1119-1125. https://doi.org/10.1121/1.381212

Beutel, M. E., Jünger, C., Klein, E. M., Wild, P., Lackner, K., Blettner, M., Binder, H., Michal, M., Wiltink, J., Brähler, E., & Münzel, T. (2016). "Noise annoyance is associated with depression and anxiety in the general population- the contribution of aircraft noise." *PLoS ONE*, *11*.5: e0155357. https://doi.org/10.1371/journal.pone.0155357

Bhiwapurkar, M. K., Saran, V. H., & Harsha, S. P. (2011). “Objective and subjective responses of seated subjects while reading Hindi newspaper under multi axis whole-body vibration.” *International Journal of Industrial Ergonomics*, *41*(6), 625–633. https://doi.org/10.1016/j.ergon.2011.06.004
Bickel, P., Diggle, P., Fienberg, S., Krickeberg, K., Olkin, I., Wermuth, N., & Zeger, S. (2009). “The elements of statistical learning: data mining, inference, and prediction.” *Journal of the American Statistical Association*, *99*:466, 567-567, https://doi.org/10.1198/jasa.2004.s339
Bishop, C. M., & Nasser M. Nasrabadi. (2002). “Pattern recognition and machine learning.” *Springer google schola*, *2*: 1122-1128.
Bohman, K., Osvalder, A.-L., Ankartoft, R., & Alfredsson, S. (2019). “A comparison of seat belt fit and comfort experience between older adults and younger front seat passengers in cars.” *Traffic injury prevention, 20*.sup2: S7-S12. https://doi.org/10.1080/15389588.2019.1639159
Bolin, K., Nilsson, M. E., & Khan, S. (2010). “The potential of natural sounds to mask wind turbine noise.” *Acta Acustica United with Acustica*, *96*(1), 131–137. https://doi.org/10.3813/AAA.918264
Branton, P. (1969). “Behaviour, Body Mechanics and Discomfort.” *Ergonomics*, *12*(2), 316–327. https://doi.org/10.1080/00140136908931055
Caird, J. K., Willness, C. R., Steel, P., & Scialfa, C. (2008). “A meta-analysis of the effects of cell phones on driver performance.” *Accident Analysis and Prevention*, *40*(4), 1282–1293. https://doi.org/10.1016/j.aap.2008.01.009
Carroll, J. B., Osgood, C. E., Suci, G. J., & Tannenbaum, P. H. (1959). “The Measurement of Meaning.” *Language*, *35*(1), 58. https://doi.org/10.2307/411335
Christopher J. Plack. (2018). “*The sense of hearing*.” Routledge, 3rd Edition. https://doi.org/10.4324/9781315208145.
Cieslak, M., Kanarachos, S., Blundell, M., Diels, C., Burnett, M., & Baxendale, A. (2020). “Accurate ride comfort estimation combining accelerometer measurements, anthropometric data and neural networks.” *Neural Computing and Applications*, *32*(12), 8747–8762. https://doi.org/10.1007/s00521-019-04351-1
Clark, C., Martin, R., Van Kempen, E., Alfred, T., Head, J., Davies, H. W., Haines, M. M., Barrio, I. L., Matheson, M., & Stansfeld, S. A. (2006). “Exposure-effect relations between aircraft and road traffic noise exposure at school and reading comprehension: The RANCH project.” *American Journal of Epidemiology*, *163*.1: 27-37. https://doi.org/10.1093/aje/kwj001
Corlett, E. N., & Bishop, R. P. (1976). “A technique for assessing postural discomfort.” *Ergonomics*, *19*(2), 175–182. https://doi.org/10.1080/00140137608931530
De Groot, S., De Winter, J. C. F., García, J. M. L., Mulder, M., & Wieringa, P. A. (2011). “The effect of concurrent bandwidth feedback on learning the lane-keeping task in a driving simulator.” *Human Factors*, *53*(1), 50–62. https://doi.org/10.1177/0018720810393241
De Looze, M. P., Kuijt-Evers, L. F. M., & Van Dieën, J. (2003). “Sitting comfort and discomfort and the relationships with objective measures.” *Ergonomics*, Vol. 46, Issue 10, pp. 985–997. https://doi.org/10.1080/0014013031000121977
Di, G. Q., Li, Z. G., Zhang, B. J., & Shi, Y. (2011). “Adjustment on subjective annoyance of low frequency noise by adding additional sound.” *Journal of Sound and Vibration*, *330*(23), 5707–5715. https://doi.org/10.1016/j.jsv.2011.06.014
Dickson, C., & Bolin, K. (2014). “Continuous judgment by category-ratio scaling of aircraft noise.” *Applied Acoustics*, *84*, 3–8. https://doi.org/10.1016/j.apacoust.2014.02.013
Du, X., Sun, C., Zheng, Y., Feng, X., & Li, N. (2021). “Evaluation of vehicle vibration comfort using deep learning.” *Measurement: Journal of the International Measurement Confederation*, *173*. https://doi.org/10.1016/j.measurement.2020.108634
Eberhard Zwicher, H. F. (1977). “Psycho-Acoustics: Facts and Models.” *The Musical Times*, Vol. 118, Issue 1617. https://doi.org/10.2307/959984
Edworthy, J., & Hellier, E. (2000). “Auditory warnings in noisy environments.” *Noise and Health*, *2.6*: 27-39.

Edworthy, J., & Stanton, N. (1995). “A user-centred approach to the design and evaluation of auditory warning signals: 1.” Methodology. *Ergonomics*, *38*(11), 2262–2280. https://doi.org/10.1080/00140139508925267

Ellermeier, W., Zeitler, A., & Fastl, H. (2004). “Impact of source identifiability on perceived loudness.” *Proc. of Proc. Int. Congress on Acoustics ICA 2004, 18. Intern. Congress on Acoustics, Kyoto, Japan.*

Fang, Y., Zhang, T., Chen, F., & Guo, R. (2015). “A subjective and objective evaluation model for psychoacoustical quality of electric vehicle noise.” *Journal of Xi'an Jiaotong University*, *49*(8), 97–101. https://doi.org/10.7652/xjtuxb201508016

Fastl, H. (2006). “Psychoacoustic basis of sound quality evaluation and sound engineering.” *13th International Congress on Sound and Vibration, ICSV 2006*, *1*, 59–74.

Fastl, H., & Zwicker, E. (2007a). “Psychoacoustics: Facts and models”. *Springer Science & Business Media*. https://doi.org/10.1007/978-3-540-68888-4

Feng, Z. C., Gu, P., Chen, Y., & Li, Z. (2009). “Modeling and experimental investigation of tire cavity noise generation mechanisms for a rolling tire.” *SAE International Journal of Passenger Cars - Mechanical Systems*, *2*(1), 1414–1423. https://doi.org/10.4271/2009-01-2104

Fitzpatrick, C. D., Samuel, S., & Knodler, M. A. (2016). “Evaluating the effect of vegetation and clear zone width on driver behavior using a driving simulator.” *Transportation Research Part F: Traffic Psychology and Behaviour*, *42*, 80–89. https://doi.org/10.1016/j.trf.2016.07.002

Frank, M., Sontacchi, A., Brandl, S., & Höldrich, R. (2014). “Sound for Electric Cars: What can we learn from combustion engines?” *6th Congress of Alps-Adria Acoustics Assosiation.*

Gao, Y., Tang, R., Liang, J., Shen, S., & Sun, H. (2010). “Evaluation of vehicle ride comfort based on neural network.” *Sixth International Symposium on Precision Engineering Measurements and Instrumentation*, *7544*, 754407. https://doi.org/10.1117/12.885814

Genell, A., Västfjäll, D., Kleiner, M., & Hedlund, A. (2006). “Components in evaluation of complex interior truck sounds.” *Journal of Low Frequency Noise Vibration and Active Control*, *25*(4), 227–237. https://doi.org/10.1260/026309206779884865

Gerber, M. A., Schroeter, R., & Vehns, J. (2019). “A Video-Based Automated Driving Simulator for Automotive UI Prototyping, UX and Behaviour.” *Proceedings of the 11th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 14–23. https://doi.org/10.1145/3342197.3344533

Giacomin, J., & Woo, Y. J. (2005). “Beyond comfort: information content and perception enhancement.” *Automobiltechnische Zeitschrift*, *107*(5), 422–429.

Glasberg, B. R., & Moore, B. C. J. (2002). “A model of loudness applicable to time-varying sounds.” *Journal of the Audio Engineering Society, 50*(5), 331-342.

Govindswamy, K., & Eisele, G. (2011). “Sound character of electric vehicles.” *SAE Technical Papers*. https://doi.org/10.4271/2011-01-1728

Grandjean, E., & Kroemer, K. H. E. (1997). “Fitting the task to the human: a textbook of occupational ergonomics.” CRC press.

Griffin, M. J., & Erdreich, J. (1991). “Handbook of Human Vibration.” *The Journal of the Acoustical Society of America*. https://doi.org/10.1121/1.401606

Guski, R., Felscher-Suhr, U., & Schuemer, R. (1999). “The concept of noise annoyance: How international experts see it.” *Journal of Sound and Vibration*, *223*(4), 513–527. https://doi.org/10.1006/jsvi.1998.2173

Hall, D. A., Irwin, A., Edmondson-Jones, M., Phillips, S., & Poxon, J. E. W. (2013). “An exploratory evaluation of perceptual, psychoacoustic and acoustical properties of urban soundscapes.” *Applied Acoustics*, *74*(2), 248–254. https://doi.org/10.1016/j.apacoust.2011.03.006

Harrison, M. (2004). “Vehicle Refinement: Controlling Noise and Vibration in Road Vehicles.” *Vehicle Refinement: Controlling Noise and Vibration in Road Vehicles*. Elsevier. https://doi.org/10.1016/B978-0-7506-6129-4.X5000-7

Hart, S. G. (1988). "Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research." *Human Mental Workload/Elsevier*.

Hartwich, F., Witzlack, C., Beggiato, M., & Krems, J. F. (2019). "The first impression counts – A combined driving simulator and test track study on the development of trust and acceptance of highly automated driving." *Transportation Research Part F: Traffic Psychology and Behaviour*, *65*, 522–535. https://doi.org/10.1016/j.trf.2018.05.012

Hassan, R., & McManus, K. (2002). "Perception of low frequency vibrations by heavy vehicle drivers." *Journal of Low Frequency Noise Vibration and Active Control*, Vol. 21, Issue 2, pp. 65–76. https://doi.org/10.1260/026309202761019516

He, L. C., Zuo, S. G., He, R., & Chen, R. F. (2010). "Analysis of noise and vibration for a new pure electrical vehicle." *The 3rd International Conference on Advanced Computer Theory and Engineering (ICACTE), Vol. 1, pp. V1-435. IEEE*. https://doi.org/10.1109/ICACTE.2010.5578981

He, S., Miller, J., Peddi, V., Omell, B., & Gandham, M. (2021). "Active Masking of Tonal Noise using Motor-Based Acoustic Generator to Improve EV Sound Quality." *SAE Technical Papers*. https://doi.org/10.4271/2021-01-1021

Helander, M. G., & Zhang, L. (1997). "Field studies of comfort and discomfort in sitting." *Ergonomics*, *40*(9), 895–915. https://doi.org/10.1080/001401397187739

Hock, P., Kraus, J., Babel, F., Walch, M., & Martin, E. R. (2018). "How to Design Valid Simulator Studies for Investigating User Experience in Automated Driving – Review and Hands-On Considerations." *Proceedings of the 10th International Conference on Automotive User Interfaces and Interactive Vehicular Applications* (pp. 105-117). https://doi.org/10.1145/3239060.3239066

Hoffmann, A. (2016). "Auralization, Perception and Detection of Tyre–Road Noise." *Chalmers University of Technology (Sweden).*

Huang, Y. (2012). "Human response to combined noise and vibration." *University of Southampton, Faculty of Engineering and the Environment*, Doctoral Thesis, 195pp. http://eprints.soton.ac.uk/348814/

Huang, Y., & Griffin, M. J. (2009). "Nonlinearity in apparent mass and transmissibility of the supine human body during vertical whole-body vibration." *Journal of Sound and Vibration*, *324*(1–2), 429–452. https://doi.org/10.1016/j.jsv.2009.02.017

Ishiyama, T., & Hashimoto, T. (2000). "Impact of sound quality on annoyance caused by road traffic noise: an influence of frequency spectra on annoyance." *JSAE Review*, *21*(2), 225–230. https://doi.org/10.1016/S0389-4304(99)00090-9

ISO 2631-1. (1997). ISO 2631-1: "Mechanical Vibration and Shock Evaluation." *International Standards Organization*.

Janssen, S. A., Centen, M. R., Vos, H., & Van Kamp, I. (2014). "The effect of the number of aircraft noise events on sleep quality." *Applied Acoustics*, *84*, 9–16. https://doi.org/10.1016/j.apacoust.2014.04.002

Jeon, J. Y., Lee, P. J., You, J., & Kang, J. (2010). "Perceptual assessment of quality of urban soundscapes with combined noise sources and water sounds." *The Journal of the Acoustical Society of America, 127(3),* 1357-1366. https://doi.org/10.1121/1.3298437

Jeon, J. Y., You, J., Jeong, C. Il, Kim, S. Y., & Jho, M. J. (2011). "Varying the spectral envelope of air-conditioning sounds to enhance indoor acoustic comfort." *Building and Environment*, *46*(3), 739–746. https://doi.org/10.1016/j.buildenv.2010.10.005

Kaderli, F., & Gomes, H. M. (2015). "Vibration analysis based on health and comfort levels on ride vehicles." *International Journal of Vehicle Noise and Vibration*, *11*(3–4), 238–254. https://doi.org/10.1504/IJVNV.2015.075166

Kamra, A., Raina, S., Maheshwari, P., Agarwal, A., & Latkar, P. (2017). "Study and proposals for improving static comfort in automotive seating." *SAE Technical Papers*, *No. 2017-01-1389*. https://doi.org/10.4271/2017-01-1389

Karikomi, T., Itou, K., Okubo, T., & Fujimoto, S. (2006). "Development of the shaking vibration control for electric vehicles." *SICE-ICASE International Joint Conference*, 2434–2439. https://doi.org/10.1109/SICE.2006.315138

Kilincsoy, U., Wagner, A., Vink, P., & Bubb, H. (2016). "Application of ideal pressure distribution in development process of automobile seats." *Work*. https://doi.org/10.3233/WOR-162350

Kolich, M., Seal, N., & Taboun, S. (2004). "Automobile seat comfort prediction: Statistical model vs. artificial neural network." *Applied Ergonomics*, *35*(3), 275–284. https://doi.org/10.1016/j.apergo.2004.01.007

Kropp, W., Sabiniarz, P., Brick, H., & Beckenbauer, T. (2012). "On the sound radiation of a rolling tyre." *Journal of Sound and Vibration*, *331*(8), 1789–1805. https://doi.org/10.1016/j.jsv.2011.11.031

Kyung, G., & Nussbaum, M. A. (2009). "Specifying comfortable driving postures for ergonomic design and evaluation of the driver workspace using digital human models." *Ergonomics*, Vol. 52, Issue 8, 939–953. https://doi.org/10.1080/00140130902763552

Landström, U., Åkerlund, E., Kjellberg, A., & Tesarz, M. (1995). "Exposure levels, tonal components, and noise annoyance in working environments." *Environment International*. https://doi.org/10.1016/0160-4120(95)00017-F

Leite, R. P., Paul, S., & Gerges, S. N. Y. (2009). "A sound quality-based investigation of the HVAC system noise of an automobile model." *Applied Acoustics*, *70*(4), 636–645. https://doi.org/10.1016/j.apacoust.2008.06.010

Lennström, D., & Nykänen, A. (2015). "Interior sound of today's electric cars: Tonal content, levels and frequency distribution." *SAE Technical Papers*, *No. 2015-01-2367*. https://doi.org/10.4271/2015-01-2367

Li, C., Sanchez, R. V., Zurita, G., Cerrada, M., Cabrera, D., & Vásquez, R. E. (2016). "Gearbox fault diagnosis based on deep random forest fusion of acoustic and vibratory signals." *Mechanical Systems and Signal Processing*, *76:* 283–293. https://doi.org/10.1016/j.ymssp.2016.02.007

Lin, K. Y., Hwang, J. R., Chang, S. H., Fung, C. P., & Chang, J. M. (2006). "System dynamics and ride quality assessment of automobile. " *SAE Technical Papers*. *SAE Technical Paper*. https://doi.org/10.4271/2006-01-1225

Maharana, K., Mondal, S., & Nemade, B. (2022). "A review: Data pre-processing and data augmentation techniques." *Global Transitions Proceedings*, *3*(1), 91–99. https://doi.org/10.1016/j.gltp.2022.04.020

Makris, M. (2023). "How Does it Feel and How is it Measured? Assessing Sitting Comfort and Postures of Rear-Seated Car Passengers in Stationary and Driven Scenarios Over Time." *Chalmers Tekniska Hogskola (Sweden).*

Makris, M., Osvalder, A., Johansson, M., & Borell, J. (2024). "Unveiling the Complexity of Car Ride Comfort: A Holistic Model." *Advances in Human Factors of Transportation*, *148*. https://doi.org/10.54941/ahfe1005257

Manawadu, U., Ishikawa, M., Kamezaki, M., & Sugano, S. (2015). "Analysis of individual driving experience in autonomous and human-driven vehicles using a driving simulator." *IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM*, *2015-Augus*, 299–304. https://doi.org/10.1109/AIM.2015.7222548

Mansfield, N. J. (2001). "Localized vibration at the automotive seat-person interface." *The 2001 International Congress and Exhibition on Noise Control Engineering, 27–30*.

Matsumoto, Y., & Griffin, M. J. (1998). "Dynamic response of the standing human body exposed to vertical vibration: influence of posture and vibration magnitude." *Journal of Sound and Vibration*, *212*(1), 85–107. https://doi.org/10.1006/jsvi.1997.1376

Miedema, H. M. E., & Vos, H. (1999). "Demographic and attitudinal factors that modify annoyance from transportation noise." *The Journal of the Acoustical Society of America*, *105*(6), 3336–3344. https://doi.org/10.1121/1.424662

Moore, B. C. J. (2012). "An introduction to the psychology of hearing." *Brill*.

Moorhouse, A. T., Waddington, D. C., & Adams, M. D. (2008). "The effect of fluctuations on the perception of low frequency sound." *Noise Notes*, *6*(4), 31–40. https://doi.org/10.1260/147547307783791872
Morioka, M., & Griffin, M. J. (2006). "Magnitude-dependence of equivalent comfort contours for fore-and-aft, lateral and vertical whole-body vibration." *Journal of Sound and Vibration*, *298*(3), 755–772. https://doi.org/10.1016/j.jsv.2006.06.011
Morioka, M., & Griffin, M. J. (2009). "Equivalent comfort contours for vertical vibration of steering wheels: Effect of vibration magnitude, grip force, and hand position." *Applied Ergonomics*, *40*(5), 817–825. https://doi.org/10.1016/j.apergo.2008.06.001
Namba, S., & Kuwano, S. (2008). "Methods for Psychoacoustics in Relation to Long-Term Sounds." *Handbook of Signal Processing in Acoustics*, 215–228. https://doi.org/10.1007/978-0-387-30441-0_15
Nawayseh, N. (2015). "Effect of the seating condition on the transmission of vibration through the seat pan and backrest." *International Journal of Industrial Ergonomics*, *45*, 82–90. https://doi.org/10.1016/j.ergon.2014.12.005
Nawayseh, N., & Griffin, M. J. (2012). "Power absorbed during whole-body fore-and-aft vibration: Effects of sitting posture, backrest, and footrest." *Journal of Sound and Vibration, 331*(1), 252-262. https://doi.org/10.1016/j.jsv.2011.08.015
Nguyen, T., Nguyen-Phuoc, D. Q., & Wong, Y. D. (2021). "Developing artificial neural networks to estimate real-time onboard bus ride comfort." *Neural Computing and Applications*, *33*(10), 5287–5299. https://doi.org/10.1007/s00521-020-05318-3
Nilsson, M. E. (2007). "A-weighted sound pressure level as an indicator of short-term loudness or annoyance of road-traffic sound." *Journal of Sound and Vibration*, *302*(1–2), 197–207. https://doi.org/10.1016/j.jsv.2006.11.010
Öhrström, E., Skånberg, A., Svensson, H., & Gidlöf-Gunnarsson, A. (2006). "Effects of road traffic noise and the benefit of access to quietness." *Journal of Sound and Vibration*, *295*(1–2), 40–59. https://doi.org/10.1016/j.jsv.2005.11.034
Osvalder, A. L., Bohman, K., Lindman, M., & Ankartoft, R. (2019). "Seat belt fit and comfort for older adult front seat passengers in cars." *Conference Proceedings International Research Council on the Biomechanics of Injury, IRCOBI*, 32–43.
Ouis, D. (2001). "Annoyance from road traffic noise: A review." *Journal of environmental psychology, 21(1), 101-120.* https://doi.org/10.1006/jevp.2000.0187
Paddan, G. S., & Griffin, M. J. (2002). "Evaluation of whole-body vibration in vehicles." *Journal of Sound and Vibration*, *253*(1), 195–213. https://doi.org/10.1006/jsvi.2001.4256
Pawlaczyk-Luszczynska, M., & Dudarewicz, A. (2020). "Impact of very high-frequency sound and low-frequency ultrasound on people - The current state of the art." *International Journal of Occupational Medicine and Environmental Health*, *33*(4), 389–408. https://doi.org/10.13075/IJOMEH.1896.01586
Pelmear, P., & Benton, S. (2003). "A Review of Published Research on Low Frequency Noise and its Effects." *UK Department for Environment, Food and Rural Affairs*. https://doi.org/EPG1/2/50.
Persson Waye, K., & Rylander, R. (2001). "The prevalence of annoyance and effects after long-term exposure to low-frequency noise." *Journal of Sound and Vibration*, *240*(3), 483–497. https://doi.org/10.1006/jsvi.2000.3251
Qatu, M. S. (2012). "Recent research on vehicle noise and vibration." *International Journal of Vehicle Noise and Vibration*, *8*(4), 289–301. https://doi.org/10.1504/IJVNV.2012.051536
Qatu, M. S., Abdelhamid, M. K., Pang, J., & Sheng, G. (2009). "Overview of automotive noise and vibration." *International Journal of Vehicle Noise and Vibration*, *5*(1–2), 1–35. https://doi.org/10.1504/IJVNV.2009.029187
Qin, Y., Tang, X., Jia, T., Duan, Z., Zhang, J., Li, Y., & Zheng, L. (2020). "Noise and vibration suppression in hybrid electric vehicles: State of the art and challenges." *Renewable and Sustainable Energy Reviews*, *124*, 109782. https://doi.org/10.1016/j.rser.2020.109782

Rakheja, S., Stiharu, I., & Boileau, P. É. (2002). "Seated occupant apparent mass characteristics under automotive postures and vertical vibration." *Journal of Sound and Vibration*, *253*(1), 57–75. https://doi.org/10.1006/jsvi.2001.4249

Roussarie, V., Siekierski, E., Viollon, S., Ségrétain, S., & Bojago, S. (2005). "What's so hot about sound? - Influence of HVAC sounds on thermal comfort." *International Congress on Noise Control Engineering 2005, 4*, 3559–3568.

Sandberg, U. (2001). "Tyre/road noise: myths and realities." *The National Road and Transport Research Institute*.

Sandberg, U., & Ejsmont, J. (2002). "Tyre/road noise: myths and realities." *The National Road and Transport Research Institute.*

Sarker, I. H. (2021). "Machine Learning: Algorithms, Real-World Applications and Research Directions." *SN Computer Science*, Vol. 2, Issue 3. Springer. https://doi.org/10.1007/s42979-021-00592-x

Sarrazin, M., Janssens, K., & Van Der Auweraer, H. (2012). "Virtual Car Sound Synthesis Technique for Brand Sound Design of Hybrid and Electric Vehicles." *SAE Technical Papers*, No. 2012-36-0614. https://doi.org/10.4271/2012-36-0614

Schmidt, J., Braunagel, C., Stolzmann, W., & Karrer-Gauss, K. (2016). "Driver drowsiness and behavior detection in prolonged conditionally automated drives." *IEEE Intelligent Vehicles Symposium, Proceedings*, *2016* (Iv), 400–405. https://doi.org/10.1109/IVS.2016.7535417

Sezgin, A., & Arslan, Y. Z. (2012). "Analysis of the vertical vibration effects on ride comfort of vehicle driver." *Journal of Vibroengineering*, *14*(2), 559–571.

Sheng, G. (2012). "Vehicle noise, vibration, and sound quality." *SAE international.* http://doi.org/10.4271/R-400

Singh, A., Narina Thakur, & Aakanksha Sharma. (2016). "A Review of Supervised Machine Learning Algorithms." *The 3rd International Conference on Computing for Sustainable Global Development*, 1310–1315.

Singh, A., Nawayseh, N., Singh, H., Dhabi, Y. K., & Samuel, S. (2023). "Internet of agriculture: Analyzing and predicting tractor ride comfort through supervised machine learning." *Engineering Applications of Artificial Intelligence*, *125*(June), 106720. https://doi.org/10.1016/j.engappai.2023.106720

Skagerstrand, Å., Köbler, S., & Stenfelt, S. (2017). "Loudness and annoyance of disturbing sounds–perception by normal hearing subjects." *International Journal of Audiology*, *56*(10), 775–783. https://doi.org/10.1080/14992027.2017.1321790

Stelrnachowicz, P. G., Beauchaine, K. A., Kalberer, A., & Jesteadt, W. (1989). "Normative thresholds in the 8- to 20-kHz range as a function of age." *Journal of the Acoustical Society of America*, *86*(4), 1384–1391. https://doi.org/10.1121/1.398698

Subedi, J. K., Yamaguchi, H., Matsumoto, Y., & Ishihara, M. (2005). "Annoyance of low frequency tones and objective evaluation methods." *Journal of Low Frequency Noise Vibration and Active Control*, *24*(2), 81–96. https://doi.org/10.1260/0263092054531000

Taghavifar, H., & Rakheja, S. (2018). "Supervised ANN-assisted modeling of seated body apparent mass under vertical whole-body vibration." *Measurement: Journal of the International Measurement Confederation*, *127*, 78–88. https://doi.org/10.1016/j.measurement.2018.05.092

Takahashi, Y., Kanada, K., & Yonekawa, Y. (2002). "The relationship between vibratory sensation and body surface vibration induced by low-frequency noise." *Journal of Low Frequency Noise Vibration and Active Control*, *21*(2), 87–100. https://doi.org/10.1260/026309202761019534

Talay, E., & Altinisik, A. (2019). "The effect of door structural stiffness and flexural components to the interior wind noise at elevated vehicle speeds." *Applied Acoustics*, *148*, 86–96. https://doi.org/10.1016/j.apacoust.2018.12.005

Toward, M. G. R., & Griffin, M. J. (2009). "Apparent mass of the human body in the vertical direction: Effect of seat backrest." *Journal of Sound and Vibration*, *327*(3–5), 657–669. https://doi.org/10.1016/j.jsv.2009.07.012

Toward, M. G. R., & Griffin, M. J. (2011). "Apparent mass of the human body in the vertical direction: Inter-subject variability." *Journal of Sound and Vibration*, *330*(4), 827–841. https://doi.org/10.1016/j.jsv.2010.08.041
van Veen, S. A. T., Orlinskiy, V., Franz, M., & Vink, P. (2015). "Investigating car passenger well-being related to a seat imposing continuous posture variation." *Journal of Ergonomics 5*(3).
Vieira, T. (2020). "Tyre/road interaction: a holistic approach to the functional requirements of road surfaces regarding noise and rolling resistance." *KTH Royal Institute of Technology*.
Von Gierke, H. E., & RR, C. (1961). "The biodynamics of human response to vibration and impact." *Industrial medicine & surgery, 32, 30-32*.
Wang, D., Jiang, M., He, K., Li, X., & Li, F. (2020a). "Study on vibration suppression method of vehicle with engine start-stop and automatic start-stop." *Mechanical Systems and Signal Processing*, *142*, 106783. https://doi.org/10.1016/j.ymssp.2020.106783
Wang, X., Osvalder, A. L., & Höstmad, P. (2023). "Influence of Sound and Vibration on Perceived Overall Ride Comfort - A Comparison between an Electric Vehicle and a Combustion Engine Vehicle." *SAE International Journal of Vehicle Dynamics, Stability, and NVH*, *7*(2), 1–19. https://doi.org/10.4271/10-07-02-0010
Wang, X., Osvalder, A. L., Höstmad, P., & Johansson, I. (2020b). "Human Response to Vibrations and Its Contribution to the Overall Ride Comfort in Automotive Vehicles-A Literature Review." *SAE Technical Papers*, *No.* 2020-01-1085. https://doi.org/10.4271/2020-01-1085
Wu, X., Rakheja, S., & Boileau, P. É. (1999). "Distribution of human-seat interface pressure on a soft automotive seat under vertical vibration." *International Journal of Industrial Ergonomics*, *24*(5), 545-557. https://doi.org/10.1016/S0169-8141(98)00058-4
Xue, H., Previati, G., Gobbi, M., & Mastinu, G. (2023). "Research and Development on Noise, Vibration, and Harshness of Road Vehicles Using Driving Simulators - A Review." *SAE International Journal of Vehicle Dynamics, Stability, and NVH*, *7*(4), 555–577. https://doi.org/10.4271/10-07-04-0035
Yacouby Reda, & Axman Dustin. (2020). "Probabilistic Extension of Precision, Recall, and F1 Score for More Thorough Evaluation of Classification Models." *Proceedings of the First Workshop on Evaluation and Comparison of NLP Systems*, 79–91. http://doi.org/10.18653/v1/2020.eval4nlp-1.9
Yang, W., & Kang, J. (2005). "Acoustic comfort evaluation in urban open public spaces." *Applied Acoustics*, *66*(2), 211–229. https://doi.org/10.1016/j.apacoust.2004.07.011
Ying-jie, L., Wen-bo, L., & Cheng-jian, P. (2019). "Numerical Investigation on the Interior Wind Noise of a Passenger Car." I*nternational Journal of Mechanical and Industrial Engineering, 13*(12), 778-782.
Yu, Z., Luo, R., Niu, L., Wu, P., Wang, Y., & Hou, Z. (2023). "Momentary ride comfort evaluation of high-speed trains based on feature selection and gated recurrent unit network." *Journal of Sound and Vibration*, *558*, 117769. https://doi.org/10.1016/j.jsv.2023.117769
Yun, S., Teshima, T., & Nishimura, H. (2019). "Human-Machine Interface Design and Verification for an Automated Driving System Using System Model and Driving Simulator." *IEEE Consumer Electronics Magazine*, *8*(5), 92–98. https://doi.org/10.1109/MCE.2019.2923899
Yuxue, B., Bingchen, G., Jianjie, C., Wenzhe, C., Hang, Z., & Chen, C. (2022). "Sitting comfort analysis and prediction for high-speed rail passengers based on statistical analysis and machine learning." *Building and Environment*, *225*. https://doi.org/10.1016/j.buildenv.2022.109589
Zeitler, A., Ellermeier, W., & Fastl, H. (2004). "Significance of Meaning in Sound Quality Evaluation." *Proceedings of the 7th Joint Conference of the French Acoustic Associations*, 781–782.
Zeitler, A., & Zeller, P. (2006). "Psychoacoustic modelling of sound attributes." *SAE Technical Papers*, 724. https://doi.org/10.4271/2006-01-0098
Zhang, L., Helander, M. G., & Drury, C. G. (1996). "Identifying factors of comfort and discomfort in sitting." *Human factors, 38*(3), 377-389. https://doi.org/10.1518/001872096778701962
Zhou, Z., & Griffin, M. J. (2014). "Response of the seated human body to whole-body vertical vibration: discomfort caused by sinusoidal vibration." *Ergonomics*, Vol. 57, Issue 5, pp. 714–732. https://doi.org/10.1080/00140139.2014.898799

Zorilă, T.-C., Stylianou, Y., Flanagan, S., & Moore, B. C. J. (2016). “Effectiveness of a loudness model for time-varying sounds in equating the loudness of sentences subjected to different forms of signal processing.” *The Journal of the Acoustical Society of America*, *140*(1), 402–408. https://doi.org/10.1121/1.4955005