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Evaluating Pedestrian Perceptions and Emotional Responses to Electric and Autonomous Vehicles: The role of Signal Design

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1. Introduction

The introduction of electric vehicles (EVs) and autonomous vehicles (AVs) is leading to transformative area and to a new conception of the automotive industry, but their diffusion is not happening without raising concerns.

On one hand, electric vehicles promise to mitigate environmental concerns by reducing emissions and reliance on fossil fuels (Xu et al., 2020), with their adoption fostered by policies aimed at reducing carbon emissions and promoting sustainable transport (Faas & Baumann, 2021). However, their quietness may raise concerns to people on road, who are accustomed to the auditory cues of traditional vehicles and might not perceive EVs until they are dangerously close, thus heightening the risk of accidents. In their study, Edwards et al. (2024) indeed shows that electric or hybrid-electric vehicle collisions with pedestrians is on average twice as likely as with traditional vehicles. It is thus evident how this has implications for the user-vehicle interaction, raising concerns and compromising a holistic sense of safety (Bazilinskyy et al., 2023), despite regulatory frameworks such as the Acoustic Vehicle Alert System (AVAS) mandating artificial sounds (Faas et al., 2020).

At the same time, a wide range of stakeholders, including technology companies, automotive manufacturers, regulatory bodies, and research institutions, are investing in the AV industry. Key players in the industry, including tech firms like Google (Waymo), Tesla, Uber, and Baidu, strive to retain their position. Traditional automakers such as Ford, General Motors, and BMW are also advancing AV capabilities, often through partnerships or acquisitions. Additionally, research institutions and universities contribute by addressing technological challenges and public acceptance of AVs (Faas et al., 2020).
Autonomous vehicles have yet to reach the same level of maturity of EVs. They rely on advanced sensors and algorithms for navigation with decision-making capabilities to function with little to no human involvement (Hensch et al., 2020). The deployment of AVs could reduce the number of accidents and save lives by removing human drivers' mistake (Yuen et al., 2020), which is responsible for approximately 94% of traffic accidents (National Highway Traffic Safety Administration, 2019). However, the absence of a driver radically changes the way of interaction with these vehicles, with pedestrians experiencing heightened uncertainty and discomfort due to the impossibility of relying on explicit cues when making crossing decisions (Faas et al., 2020). This becomes even more concerning in traffic situations, such as at unsignalized intersections or crosswalks.

Both vehicle concepts bring along interactions issues, and innovative technological solutions in external human-machine interfaces (eHMI) design may represent a new possibility for enhancing pedestrian safety and interaction with EVs and AVs. For this reason, various external human-machine interfaces have been proposed that communicate the intent of vehicles to vulnerable road users (VRUs), such as pedestrians or cyclists. However, a consensus on which eHMI concept is the most suitable for intent communication remains elusive (Oudshoorn, et al., 2021).

Research so far has been mainly focused on primary users (Driver/Passenger). However, it is also important to consider the vulnerable road users. These users do not choose to interact with such vehicles but are often required to when they encounter them on the road. Since they may have limited knowledge about the new technologies these vehicles use, it is essential to ensure they can engage with them smoothly and safely (Faas & Baumann, 2021).

Moreover, past research has mainly focused on either technological aspect of eHMIs or the psychological aspects of pedestrian behaviour in isolation. Integrating these perspectives instead could provide a more holistic understanding of how to design effective communication systems for EVs and AVs.

Therefore, this research shifts its focus to pedestrians' perspective. The research investigates the interaction between pedestrians and eHMIs, focusing on electric and autonomous vehicles. It addresses the communication challenges posed by EVs' silent operation and the autonomous decision-making nature of AVs. By combining qualitative and quantitative methodologies, it aims to gain a holistic understanding of pedestrian behaviour and communication preferences. Data was collected through two distinct surveys tailored separately for EVs and AVs, assessing various communication methods' effectiveness. This methodology contributes to existing research by evaluating multimodal communication strategies' combined impact on pedestrian safety and trust.

2. Societal Impacts of Autonomous and Electric Vehicles: A Contextual Overview

2.1. Importance and potential impact on the society of Electric Vehicles

The electric vehicle (EV) market has been growing rapidly, driven by technological advancements, environmental concerns, and regulatory policies promoting sustainable transportation. EVs, which include battery electric vehicles and plug-in hybrid electric vehicles (PHEVs), are pivotal in reducing greenhouse gas emissions and dependency on fossil fuels. The shift toward electrification is considered one of the three major revolutions in transportation, alongside vehicle automation and shared mobility (Guo et al., 2021).

Global EV stock surpassing 14 million in 2021 with sales doubling over two years (IEA, 2022) is a great news to sustainable transportation. Figure 1 shows the forecast of sales for EVs until 2035, based on three different scenarios.

- **Stated Policies Scenario**: Reflects current policies and commitments as implemented or officially announced by governments as of the time of analysis.
- **Announced Pledges Scenario**: Assumes governments meet their announced climate and energy goals, including those not yet backed by specific policies.
- **Net Zero Emissions by 2050 Scenario**: Aims for a pathway consistent with achieving net-zero emissions globally by 2050, requiring ambitious changes and technological advancements.

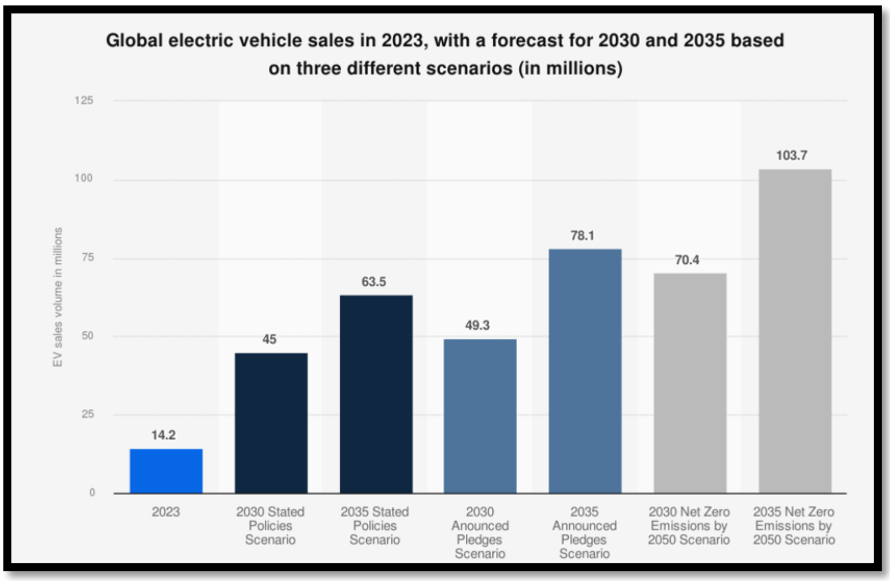


Figure 1

2.1.1. Technological Advancements

Electric vehicle technology has seen significant advancements, particularly in battery technology, which is crucial for enhancing performance and reducing costs. Lithium-iron-phosphate batteries are gaining traction due to their lower cost and improved safety, especially in China, where they are becoming increasingly popular. These batteries are expected to capture a significant share of the global passenger EV market in the coming years (IEA, 2024; Current, 2024). Solid and semi-solid-state batteries are also emerging, promising higher charging speeds and longer lifespans. Although these technologies receive considerable attention, they are still a few years from widespread adoption (Current, 2024). Table 1 provides a list of core technologies of EVs.

Category	**Technology**	**Description**	**Advantages**	**Disadvantages**
Energy Storage	Lithium-Ion Batteries	Rechargeable batteries that power the vehicle's electric motor. Variants include NMC (Nickel Manganese Cobalt), LFP (Lithium Iron Phosphate), and NCA (Nickel Cobalt Aluminium).	High energy density, long cycle life, and established manufacturing processes.	Potential safety risks if damaged or improperly charged; performance can degrade over time. Difficult of recycling.
Energy Storage	Solid-State Batteries	Next-generation batteries using solid electrolytes instead of liquid, aiming for higher energy density and safety.	Improved safety and potentially higher energy density.	Currently in development; challenges with manufacturing scalability.
Electric Propulsion	Electric Motors	Devices that convert electrical energy into mechanical energy to drive the vehicle.	High efficiency, instant torque delivery, and fewer moving parts compared to internal combustion engines.	Dependence on rare earth materials for some motor types.
Electric Propulsion	Motor Controllers	Electronic units that manage the performance and behaviour of electric motors.	Precise control over motor functions, enhancing efficiency and performance.	Complexity in design and integration.
Charging Technology	Onboard Chargers	Converters that allow EVs to charge from standard electrical outlets by converting AC to DC power.	Convenience of charging from various power sources.	Limited by the power capacity of the onboard charger.

Charging Technology	Fast Charging Stations	High-power external chargers that provide rapid charging capabilities.	Significantly reduces charging time, enhancing convenience for long-distance travel.	Requires substantial infrastructure investment and can impact grid stability.
Vehicle Integration	Battery Management Systems (BMS)	Systems that monitor and manage battery health, performance, and safety.	Ensures optimal battery performance and longevity.	Adds complexity and cost to the vehicle's electrical system.
Vehicle Integration	Thermal Management Systems	Regulate the temperature of the battery and other components to maintain efficiency and safety.	Prevents overheating and extends component lifespan.	Requires additional components and energy consumption.
Connectivity	Telematics Systems	Enable remote monitoring, diagnostics, and software updates.	Facilitates over-the-air updates and real-time data analysis.	Raises concerns about data security and privacy.

Table 1 - Main technologies of EVs

Globally, the EV market is experiencing robust growth, though the pace varies across regions. China, India, and France are leading in EV adoption, while growth in the United States and Germany is slower (Atlas EV Hub, 2024). BYD and Tesla are the dominant players in the market, accounting for a significant portion of global sales, with BYD recently surpassing Tesla as the leading EV brand (IEA, 2024). The intense competition, particularly in China, has led to price reductions for electric vehicles, making them more accessible to consumers (IEA, 2024).

Despite these positive trends, several barriers still hinder widespread adoption. Range anxiety, the fear of running out of battery power without access to charging stations, remains a significant concern for potential buyers (Rezvani et al., 2015). One of the main challenges is the development of more efficient and durable batteries that can provide an autonomy comparable to that of gasoline vehicles. Currently, most electric vehicles have a limited range, which may discourage potential buyers. Investment in research and development is necessary to improve battery performance and reduce costs. Another crucial challenge is the creation of a widespread and accessible charging infrastructure. Without a comprehensive network of charging points, both public and private, the adoption of electric vehicles will remain limited. Many countries are investing in charging infrastructure projects, but international coordination is needed to ensure interoperability and accessibility for all users. Although electric vehicles are considered more environmentally friendly during use, the production of batteries and the generation of electricity can have a significant environmental impact. It is essential to evaluate the entire life cycle of electric vehicles to fully understand their ecological footprint. Some studies have shown that, depending on the energy mix used for electricity production, electric vehicles may not always be more environmentally friendly than internal combustion vehicles (Sottile, 2023)

However, the long-term outlook for EV adoption is optimistic, with projections indicating that electric vehicles could account for 45% of global passenger vehicle sales by 2030 and 73% by 2040 (Atlas EV Hub, 2024). Continued advancements in battery technology and charging infrastructure, along with supportive government policies, are essential to maintaining this growth trajectory and overcoming current barriers (Atlas EV Hub, 2024; Current, 2024). Efforts to simplify charging solutions and integrate payment systems are expected to make EV ownership more convenient, further encouraging adoption (Current, 2024).

2.1.2. Economic and Environmental impact

The economic factors influencing the adoption of electric vehicles (EVs) are complex, involving the upfront purchase cost, operating expenses, and the impact of government incentives. While general EVs may typically come with a higher upfront cost versus standard internal combustion engine vehicles (ICEVs), the long-term savings with EV are undeniable and many consumers are attracted to this aspect.

The purchase price is still an obstacle to reconciling with the world of EVs. Nevertheless, since EVs have lower fuel and maintenance costs, studies have supported that TCO for EVs can be lower than ICEVs. A report by the International Council on Clean Transportation (ICCT) pointed out that, because of lower operating costs, especially when fuel prices are high, EVs may lead to significant savings over a five-year period. Also, the cost of electric energy is always lower than the cost of fuel. This is highlighted in a study by Bloomberg New Energy Finance (BNEF) found that, in many markets, the fuel cost savings for EVs can offset the higher purchase price within a few years of ownership. Government incentives play a crucial role in reducing the effective purchase price and encouraging adoption. These incentives include tax credits, rebates, and exemptions from registration fees.

The cost of lithium-ion batteries, a major component of EV costs, has been decreasing rapidly. According to BloombergNEF, battery prices have dropped by 89% from 2010 to 2020, which is expected to continue driving down the overall cost of EVs, making them more competitive with ICEVs without subsidies.

From an environmental perspective, EVs offer a smaller carbon footprint over their lifetime compared to traditional vehicles, even when accounting for the emissions from manufacturing and electricity generation for charging (Autoblog, 2024). However, the production of EV batteries involves significant environmental challenges, including the extraction and processing of raw materials like lithium, cobalt, and nickel. The demand for these materials has increased substantially, driving up production but also resulting in overcapacity, which has helped reduce material prices (IEA, 2024). Additionally, the disposal of batteries at the end of their life poses an environmental challenge.

One of the most significant environmental benefits of EVs is their ability to reduce emissions. The transportation sector is a major contributor to greenhouse gas emissions, and the shift to EVs powered by renewable energy can significantly lower these emissions. Unlike ICEVs, which rely on fossil fuels and produce emissions throughout their lifecycle, EVs offer a cleaner alternative when powered by renewable sources such as wind or solar energy. This transition supports global efforts to reduce reliance on fossil fuels and lower carbon footprints, making EVs a crucial component of sustainable transportation strategies. EVs also contribute to improved air quality by eliminating tailpipe emissions, which are a major source of urban air pollution. This is particularly important in densely populated areas, where ICEVs contribute to smog and other harmful pollutants. By reducing these emissions, EVs help decrease the incidence of respiratory diseases and other health problems associated with poor air quality (Zhang et al., 2020). The environmental benefits of EVs are further amplified by advancements in energy storage and battery technologies. These improvements enhance the efficiency and sustainability of EVs, allowing for greater integration with renewable energy grids. Controlled charging strategies can optimize EV energy use, aligning charging times with periods of low grid demand and high renewable energy availability. This not only improves the efficiency of the electricity grid but also maximizes the environmental benefits of using renewable energy to power EVs. While the initial production of EVs may involve higher emissions compared to ICEVs due to battery manufacturing, the overall lifecycle emissions of EVs are typically lower. This is especially true when EVs are powered by clean energy sources throughout their use. As renewable energy becomes more prevalent, the environmental advantages of EVs over ICEVs are expected to increase, further supporting the transition to a more sustainable transportation system

2.1.3. Societal Impact: Pedestrian's perspective on EVs

Traditional vehicles rely on driver cues such as eye contact and gestures, necessitating new communication methods to convey vehicle intentions to pedestrians (Faas & Baumann, 2021). EVs, while similar to conventional vehicles, pose unique challenges due to their quieter operation, making it difficult for pedestrians to detect them, thereby raising safety concerns (Xu et al., 2020).

Electric vehicles (EVs) are distinct from ICEVs primarily due to their quiet operation, which is both an advantage and a challenge. The absence of engine noise is beneficial for reducing noise pollution in urban areas but poses significant risks for pedestrian safety. The quietness of EVs can lead to increased difficulty for pedestrians in detecting approaching vehicles, thereby increasing the potential for accidents. This is particularly important in environments where visual cues might be insufficient, such as in areas with limited visibility or where pedestrians are distracted (Bergman et al., 2017). The reduced noise from EVs can lead to situations where pedestrians are unaware of an approaching vehicle, especially at low speeds, which are common in pedestrian-heavy areas. Research by Faas and Baumann (2021) highlights the critical role of Acoustic Vehicle Alerting Systems (AVAS) in bridging this communication gap. These systems, which emit artificial sounds to mimic the noise of traditional vehicles, have been found to significantly improve pedestrian awareness and safety. The integration of AVAS has been mandated in many regions.

These systems aim to mimic the noise produced by traditional vehicles, thereby providing the necessary auditory signals to pedestrians. The introduction of AVAS is intended to restore the critical sound cues that pedestrians use to assess the presence and movement of vehicles, effectively bridging the communication gap caused by the inherent silence of EVs. Rezvani, et al. (2015) provide further evidence supporting the effectiveness of AVAS by examining consumer perceptions and safety outcomes related to EV adoption. They highlight that the presence of sound-emitting systems not only enhances pedestrian safety but also improves the general acceptance of EVs by addressing concerns related to silent operation. This research underscores the necessity for manufacturers to prioritize pedestrian communication strategies in EV design to facilitate safer urban environments.

The adoption of electric vehicles also raises ethical questions, such as economic accessibility for all segments of society and equity in access to charging infrastructure. Electric vehicles are currently more expensive than traditional cars, which may limit their accessibility to low-income populations. It is necessary to develop incentive and financing policies to make electric vehicles more accessible. Furthermore, the distribution of charging infrastructure could favour certain geographical areas at the expense of others, creating inequalities in access. It is crucial to ensure that investment policies in charging infrastructure consider the needs of all communities and promote equity. Another ethical issue concerns the geopolitical implications related to dependence on critical raw materials for battery production. The concentration of these resources in a few countries could create geopolitical tensions and influence global power balances. It is essential to diversify supply sources and promote recycling practices to reduce dependence on imports (Corzato, 2017).

2.2. Importance and potential impact on the society of Autonomous Vehicles

The introduction of autonomous vehicles is expected to bring about substantial changes in various aspects of society. This section explores the diverse implications of AVs, emphasizing their potential benefits and challenges. The potential impact of autonomous vehicles on society is profound and multifaceted. AVs offer significant benefits in terms of safety, efficiency, economic growth, and inclusivity. They have the potential to transform transportation, making it safer, more efficient, and more accessible. However, the adoption of AVs also poses challenges that require careful consideration and proactive management. Issues related to job displacement, ethical decision-making, data privacy, and cybersecurity must be addressed to ensure a smooth transition to an autonomous future (Kettles & Wang, 2020). The AV technology evolution is accelerating, with investments from automotive design giants and tech companies looking to produce solutions that will enhance traffic efficiency, safety, and accessibility for the non-driver (Yuen et al., 2020). Worldwide, in 2023 it is estimated that more than 30 million vehicles (Figure 2) with at least some form of automation on the roads (Statista, 2023).

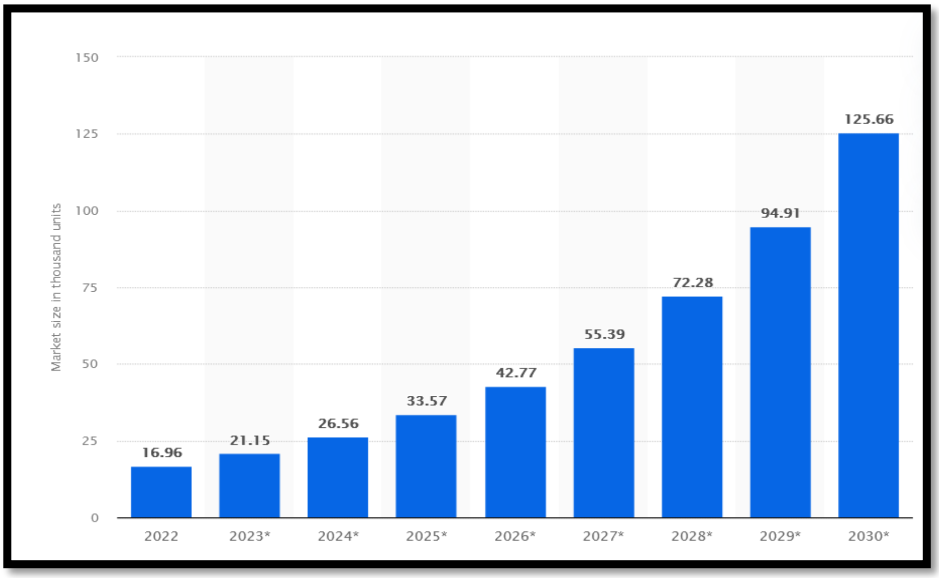


Figure 2 Number of autonomous vehicles globally in 2022, with a forecast through 2030 (in 1,000 units)

2.2.1. Technological Advancements

Autonomous vehicles, often referred to as self-driving or driverless cars, are vehicles that are capable of navigating and operating without the direct involvement of a human driver. These vehicles use a combination of sensors, software, and advanced algorithms to perceive their surroundings, make decisions, and control the vehicle's movements. The development of autonomous vehicle technology has been driven by the potential to enhance safety, improve transportation efficiency, and provide mobility solutions for individuals who may be unable to operate a traditional vehicle, such as the elderly or those with disabilities. Their development involves utilize advanced technologies such as artificial intelligence, machine learning, and sophisticated sensor systems to navigate and operate without human intervention, promise numerous societal benefits (Maeng and Cho, 2021). Autonomous vehicles (AVs) rely on a combination of advanced technologies, including sensors, artificial intelligence (AI), and machine learning algorithms. Key sensor technologies include LiDAR, which provides high-resolution 3D maps of the environment by measuring distances with laser pulses, radar, which detects objects and measures their speed and distance, functioning effectively in various weather conditions, ultrasonic sensors, used for close-range detection such as parking assistance and obstacle detection at low speeds, and cameras, which provide visual data for object recognition, lane detection, traffic sign recognition, and other critical functions. AI and machine learning play crucial roles in processing the data collected by these sensors. Perception algorithms process sensor data to identify objects, interpret traffic signals, detect lane markings, and understand the vehicle's surroundings. Decision-making algorithms make real-time decisions based on the processed data, determining the vehicle's path, speed, and responses to dynamic changes in the environment. Path planning algorithms calculate the optimal route and navigation paths for the vehicle, taking into account traffic, road conditions, and other factors. The Global Positioning System (GPS) provides accurate location data to help the vehicle navigate and stay on course. Vehicle-to-Everything (V2X) communication enables the AV to communicate with other vehicles (V2V), infrastructure (V2I), pedestrians (V2P), and networks (V2N) to share information and enhance situational awareness. High-Definition (HD) maps offer detailed and precise mapping of the environment, including road layouts, traffic signals, and other essential information that supports navigation and localization. Computer vision uses cameras and AI to interpret visual data for tasks like identifying pedestrians, vehicles, road signs, and traffic lights. These technologies work together to enable AVs to perceive their environment, make informed decisions, and navigate safely without human intervention. Table 2 provides a schematic list of core technologies of AVs

Category	Technology	Description	Advantages	Disadvantages
Data Processing	ECU (Electronic Control Units)	Electronic control units that manage multiple aspects of the vehicle, including engine, chassis, safety, and accessories.	High precision, efficiency, advanced diagnostics (OBD), future real-time updates support.	Increasing complexity with the number of ECUs.
Digital Control	Drive-by-wire	Replaces mechanical connections (e.g., brakes, accelerator) with electronic signals processed by control units.	Greater precision, reliability, durability, and safety.	Dependence on complex electronic systems.

Sensors	Lidar	Detects distances and maps the environment using light pulses, creating 2D or 3D maps in real-time.	High precision in object recognition.	High cost, sensitive to adverse weather conditions.
Sensors	Radar	Uses radio waves to detect distances and speeds of surrounding objects.	Economical, performs well in adverse weather conditions.	Lower resolution compared to Lidar.
Sensors	Ultrasound	Measures short-range distances using ultrasonic waves, useful for parking manoeuvres.	Economical, resistant to adverse weather conditions.	Limited to short range.
Sensors	Cameras	Provides high-resolution images, enabled by AI and computer vision algorithms to recognize road signs, objects, and obstacles.	High resolution, supports systems like lane keeping and emergency braking.	Sensitive to low light and adverse weather conditions.
Connectivity	In-vehicle connectivity	Internet connectivity for functions such as navigation, communication, and real-time updates.	More customization opportunities, continuous updates, integration with the digital ecosystem.	Potential risks to data privacy and security.
Advanced Systems	Artificial Intelligence (AI)	Supports functions like computer vision, sensor data processing, and autonomous decision-making.	Advanced automation, improved safety and performance.	Requires sophisticated hardware and software.

Table 2 - Main technologies of AVs

AVs are designed to perform all driving tasks, from navigating through city streets to highway driving, using a combination of technologies. The concept of autonomous vehicles has been in development for several decades, but recent advancements in technology have accelerated their progress towards becoming a practical reality. AVs promise numerous benefits, including enhanced road safety by reducing human error, increased mobility for individuals unable to drive, improved traffic flow, and environmental benefits through optimized driving patterns and reduced emissions.

The Society of Automotive Engineers (SAE) defines six levels of driving automation, ranging from Level 0 (no automation) to Level 5 (full automation):

- **Level 0 (No Automation)**: The human driver is responsible for all driving tasks.
- **Level 1 (Driver Assistance)**: The vehicle can assist with either steering or acceleration/deceleration, but not both simultaneously.
- **Level 2 (Partial Automation)**: The vehicle can control both steering and acceleration/deceleration, but the human driver must remain engaged and monitor the driving environment.
- **Level 3 (Conditional Automation)**: The vehicle can handle all driving tasks under certain conditions, but the human driver must be ready to take control when requested.
- **Level 4 (High Automation)**: The vehicle can perform all driving tasks and monitor the driving environment in specific scenarios without human intervention.
- **Level 5 (Full Automation)**: The vehicle can perform all driving tasks under all conditions without any human intervention.

Their rapid advancement has captured the attention of researchers, industry leaders, and the public alike, as these innovative solutions hold the promise of transforming the way we approach transportation. The deployment of AV technology varies across different regions. In North America, companies like Waymo and Tesla are leading the development and testing of AVs. Waymo has been testing its autonomous vehicles in multiple states and has even launched a limited commercial ride-hailing service using AVs in Arizona. In Europe, several countries have established testing grounds and regulatory frameworks to facilitate AV testing. Germany, for example, has allowed Level 4 AVs to operate on public roads under specific conditions. In Asia, China is rapidly advancing in the AV sector with companies like Baidu and AutoX conducting extensive road tests. The Chinese government is also supporting AV development through favourable policies and infrastructure investments (Rahman and Thill, 2023; Guo et al., 2021).

2.2.2. Economic and Environmental Impact

The integration of AVs into the transportation ecosystem is poised to stimulate economic growth by creating new industries and job opportunities. The development, production, and maintenance of AVs will generate employment in high-tech sectors, contributing to economic diversification and resilience. Furthermore, AVs are expected to drive the emergence of new business models such as ridesharing and mobility-as-a-service (MaaS). These models will foster innovation and entrepreneurship, providing additional economic benefits (Yuen et al., 2020).

The economic impact of AVs is multifaceted. On one hand, the production and maintenance of AVs will create jobs in manufacturing, software development, and infrastructure. On the other hand, the shift towards AVs will stimulate the growth of ancillary industries, including data management, cybersecurity, and urban planning. Moreover, the efficiency gains from AVs can lead to cost savings for businesses and consumers alike, further driving economic growth (Maeng and Cho, 2021).

Additionally, AVs have the potential to reduce the costs associated with road accidents, including healthcare expenses, legal fees, and property damage. By enhancing road safety, AVs can contribute to significant economic savings, which can be redirected towards other critical areas such as education and healthcare (Kettles and Wang, 2020).

AVs have the potential to significantly reduce the environmental footprint of transportation. By optimizing driving behaviours and enabling more efficient traffic management, AVs can lower fuel consumption and emissions. This reduction in emissions is particularly important in the context of global efforts to combat climate change. Additionally, the adoption of electric AVs can further enhance environmental benefits by reducing reliance on fossil fuels and decreasing greenhouse gas emissions (Yuen et al., 2020). Is important to remember though, that the environmental impact of AVs also depends on the broader energy grid and the sources of electricity used to charge electric AVs. For AVs to realize their full environmental potential, it is crucial that the electricity used to power them comes from renewable sources. Thus, the environmental benefits of AVs are intrinsically linked to the adoption of renewable energy sources at a societal level. Optimized driving patterns and reduced emissions from AVs can contribute to a more sustainable transportation system. A significant body of research has explored consumer attitudes, acceptance, and expectations regarding autonomous vehicles. Studies have examined factors such as perceived benefits, concerns, and the willingness to adopt this technology. Numerous studies have found that consumers generally express a positive attitude towards autonomous vehicles, recognizing the potential benefits in terms of improved safety, reduced traffic congestion, and increased accessibility for those who may have difficulty driving. However, concerns have also been raised regarding issues such as privacy, cybersecurity, liability, and the potential impact on employment in the transportation industry (Faas, Mathis, and Baumann, 2020). Autonomous vehicles can optimize driving patterns, reduce traffic congestion, and lower fuel consumption and emissions through smoother acceleration and braking.

Furthermore, AVs can contribute to more sustainable urban development. By reducing the need for parking spaces and enabling more efficient use of road infrastructure, AVs can help cities reclaim valuable land for green spaces, residential areas, and commercial development. This shift can lead to more liveable and sustainable urban environments (Maeng and Cho, 2021).

2.2.3. Societal Impact: Pedestrian perspective on AVs

One of the most significant advantages is the potential reduction in traffic accidents. Human error is a leading cause of road accidents, and AVs can significantly enhance road safety by eliminating this variable. This improvement could result in fewer fatalities and injuries both for passengers and pedestrians, leading to lower healthcare costs and a better overall quality of life (Yuen et al., 2020). In addition to enhancing safety, AVs can contribute to improved traffic flow and reduced congestion. Through optimized driving patterns and vehicle-to-vehicle communication, AVs can make more efficient use of road infrastructure, decreasing travel times and reducing the stress associated with traffic jams. This efficiency not only saves time but also translates into economic benefits, including lower fuel consumption and reduced emissions, which are crucial for environmental sustainability (Maeng and Cho, 2021). According to recent studies, human error is responsible for approximately 94% of traffic crashes, highlighting the potential for AVs to improve safety significantly (National Highway Traffic Safety Administration, 2019). Figure 3 shows that the deployment of AVs could reduce the number of accidents and save lives by removing human drivers 'mistake (Yuen et al., 2020).

AVs have the potential to transform the travel experience by allowing passengers to engage in other activities, such as working, reading, or relaxing, during their commute. Researchers have also investigated the factors that influence consumer acceptance of autonomous vehicles. These

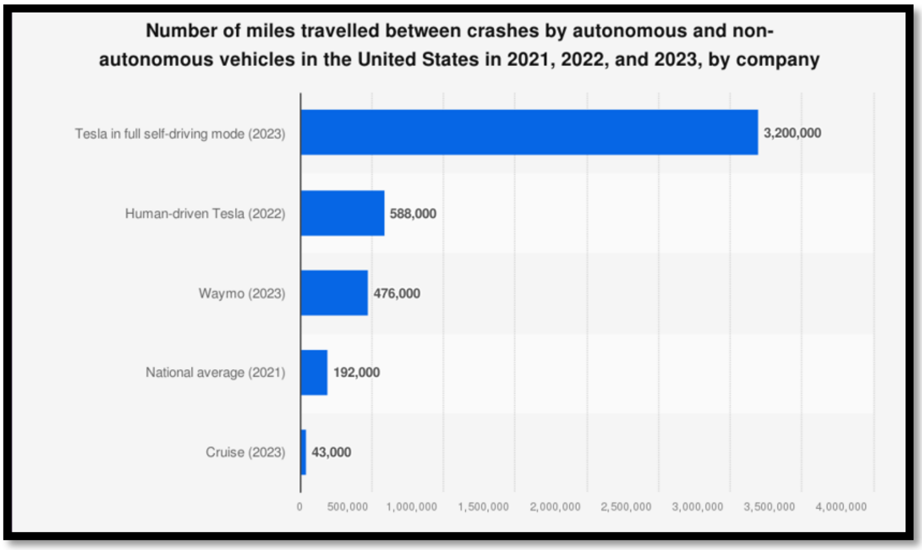


Figure 3

factors include trust in the technology, perceived usefulness, perceived ease of use, and social influence. Studies have shown that consumers who perceive autonomous vehicles as useful and easy to use are more likely to be willing to adopt the technology. Additionally, the level of trust consumers has in the safety and reliability of the technology has been identified as a key factor in determining their acceptance. In terms of inclusivity, AVs can provide mobility solutions for individuals who are unable to drive, such as the elderly, disabled, and those without a driver's license.

The potential of AVs extends beyond individual benefits to societal advantages. For instance, AVs can provide reliable transportation options for individuals who are unable to drive, such as the elderly and disabled. This inclusivity aspect highlights the broader social benefits of AV technology, as it enhances mobility and independence for these populations, thereby improving their quality of life (Kettles and Wang, 2020).

Despite their numerous advantages, the widespread adoption of AVs also presents several challenges that must be addressed. Their deployment on the streets presents challenges involving all parties. From VRU's point of view, traditional cues such as eye contact, gestures, or even driver intent (often conveyed informally through body language) are absent in AVs, creating a communication gap that must be covered. This gap becomes even more concerning in traffic situations, such as at unsignalized intersections or crosswalks. Studies have shown that pedestrians often rely on visual cues and intuitions, such as vehicle speed or trajectory, to make crossing decisions. However, these implicit cues are not always sufficient or clear when dealing with AVs. Pedestrians report increased uncertainty and discomfort, particularly when the vehicle's intent is not explicitly communicated, leading to hesitancy or risky crossing behaviours (Faas et al., 2020).

Zhao et al. (2023) involved analysing how the presence and behaviour of other pedestrians influence an individual's interaction with AVs. This study highlighted that social cues play a crucial role in decision-making processes, suggesting that AVs equipped with external human-machine interfaces (eHMIs) could benefit from mimicking or reacting to social behaviours to enhance communication effectiveness. Additionally, the role of secondary tasks in pedestrian distraction was investigated, revealing that eHMIs need to be designed to capture attention even when pedestrians are engaged in other activities. The role of social context in pedestrian behaviour when interacting with AVs has been relatively underexplored. They also examined how the behaviours of others influence individual pedestrians' interactions with AVs, suggesting that social learning can either enhance or impair pedestrian safety depending on the behaviour being modelled.

Moreover, there are concerns related to data privacy and cybersecurity. AVs rely on vast amounts of data to operate efficiently, raising questions about how this data is collected, stored, and used. Ensuring that AV systems are secure from cyber threats is essential to prevent malicious attacks that could compromise safety and privacy (Yuen et al., 2020).

From a social perspective, one major concern is the potential displacement of jobs, particularly for drivers in the transportation industry. The transition to AVs could lead to significant job losses, affecting livelihoods and prompting socioeconomic disruptions. Policymakers and industry stakeholders must proactively address these issues by implementing retraining programs and social safety nets to support workers transitioning to new roles (Kettles and Wang, 2020). Ethical considerations are also paramount in the deployment of AVs. Decisions made by autonomous systems in critical situations, such as unavoidable accidents, raise moral questions about accountability and the value of human life. For instance, if an AV must choose between two harmful outcomes, how should it decide which action to take? Establishing robust regulatory frameworks and ethical guidelines is crucial to navigate these complexities and build public trust in AV technology (Maeng and Cho, 2021).

3. Pedestrian Concerns in the Context of EVs and AVs

3.1. Importance of Trust and Safety in AV and EV Systems

Trust is a foundational element in the societal acceptance and adoption of AVs and EVs. It transcends the technical functionality of these vehicles, encompassing a broader sense of reliability and safety in diverse, real-world environments.

Trust in EVs is shaped by their unique operational characteristics, particularly their quietness. While the reduced noise of EVs provides environmental benefits, it also presents significant safety challenges. Pedestrians, especially those who rely on auditory cues, such as visually impaired individuals, may find it difficult to detect approaching EVs at low speeds. This issue heightens the potential for safety risks in urban environments. To mitigate this, artificial sound systems have been implemented, simulating traditional engine noises to enhance the detectability of EVs. Koh and Yuen (2023) argue that such auditory enhancements are not only critical for safety but also essential in cultivating trust, ensuring pedestrians feel secure when sharing spaces with EVs.

On the other hand, for AVs trust is closely tied to the vehicle's ability to effectively communicate its intentions, a requirement that becomes essential in the absence of traditional human interaction cues. Conventional non-verbal signals such as eye contact or hand gestures, which establish mutual understanding between drivers and pedestrians, are absent in AVs, potentially creating a trust deficit. To address this, eHMIs have been developed to convey the vehicle's intent through visual, auditory, or combined signals. For instance, eHMIs can indicate whether the vehicle intends to stop, yield, or proceed, offering clarity in ambiguous traffic scenarios. Research by Zhao et al. (2024) underscores the importance of eHMIs in reducing pedestrian hesitation and anxiety, thereby fostering trust. Importantly, this trust is cultivated through consistent positive experiences, where the AV operates as expected, reinforcing the pedestrian's belief in the system's safety and predictability.

The perception of trust and perceived safety is multifaceted, involving both cognitive and affective dimensions that shape pedestrian interactions with AVs and EVs. Perceived safety significantly influences pedestrian decision-making, particularly when navigating complex urban environments. Pedestrians must feel confident that AVs will act predictably and prioritize their safety. EHMIs contribute to this by reducing ambiguity, thereby improving perceived safety and facilitating more confident pedestrian behaviour (Zhao et al., 2024).

As AVs and EVs become more prevalent, pedestrian behaviour is likely to evolve through a process of adaptation. Repeated exposure to AVs and their communication signals fosters familiarity, allowing pedestrians to better interpret eHMI cues and make more informed decisions. Over time, this adaptation can lead to safer and more predictable interactions. Zhao et al. (2024) highlight that frequent exposure to AVs reduces uncertainty in crossing decisions, promoting a gradual alignment of pedestrian behaviours with the operational norms of autonomous systems.

Risk perception and trust remain central to pedestrian-vehicle interactions. The dynamic nature of trust means it can fluctuate based on contextual factors such as traffic complexity and mental workload. For example, in high-stress environments, pedestrians may rely more heavily on trust due to cognitive overload, potentially leading to risky behaviours (Zhao et al., 2023). Consequently, maintaining trust requires EVs and AVs to consistently exhibit safe and transparent behaviour across varied scenarios.

Trust and perceived safety are interdependent constructs critical to pedestrian interactions with AVs and EVs. Establishing this trust demands a combination of technological innovation, such as eHMIs and artificial sound systems, and consistent, reliable vehicle behaviour. These elements collectively enable pedestrians to feel secure and confident, fostering the broader societal acceptance of these advanced transportation technologies.

3.2. Demographic Variations in Pedestrian Safety and Trust Levels

Demographic factors play a crucial role in shaping the trust and acceptance of electric vehicles among vulnerable road users, including pedestrians, cyclists, and older adults.

Age emerges as one of the determinants, with older individuals often perceiving EVs as less safe due to their reliance on auditory cues for detecting vehicles, which are diminished in quieter EVs. This contrasts with younger populations, who are generally more adaptable to new technologies and urban infrastructures that accommodate EVs (Vladimir & Grdinić-Rakonjac, 2021). Tao et al. (2024) highlighted that older individuals and women demonstrate lower likelihoods of adopting EVs, which could derive from conservative outlooks and reduced trust in novel technologies. These groups may perceive higher risks in interactions with quieter vehicles like EVs, especially in pedestrian scenarios where auditory cues are critical.

The distinction between urban and rural residents also shapes perceptions, as those in urban areas, with higher exposure to EVs and related infrastructure, typically report greater acceptance and trust compared to rural residents, who may be less familiar with the technology and harbour scepticism about its safety or utility.(Arif Devi et al., 2023) Cultural norms and regional differences further influence acceptance; in countries with strong pedestrian rights and advanced urban planning, such as the Netherlands, trust and acceptance of EVs are higher, reflecting a combination of supportive infrastructure and societal attitudes toward innovation and sustainability. This disparity in perceptions highlights the need for targeted education and outreach programs to address rural concerns and increase awareness of EV benefits, potentially bridging the urban-rural divide in EV adoption rates (Arif Devi et al., 2023).

Social context and environmental factors shape pedestrian decision-making processes, and the neighbourhood of residence significantly influences perceptions of Electric Vehicles. Zhao et al. (2023) highlight that pedestrians often take cues from the behaviour of others, such as group crossing dynamics, which can influence individual decisions. Urban environments, characterized by higher population density and complex traffic systems, are often at the forefront of technological adoption. In these areas, residents frequently encounter challenges such as high traffic volumes, congestion, and parking scarcity, which amplify the perceived benefits of EVs. The promise of EVs to reduce emissions, offer cost savings, and contribute to sustainability resonates more strongly in cities, where concerns about air pollution and climate change are more prominent (Koh and Yuen, 2023). Additionally, urban areas typically offer greater access to the necessary infrastructure for EVs, including charging stations, well-maintained roads, and smart traffic management systems. Urban populations, being more accustomed to technological advancements, are also more likely to embrace EV innovations (Rahman and Thill, 2023).

On the other hand, rural areas present different circumstances that shape attitudes toward EV adoption. In these regions, driving environments are typically less congested, and the need for alternatives to fossil-fuel-based transportation may not seem as pressing. Limited exposure to EVs and other cutting-edge automotive technologies often leads to a lack of familiarity and trust in these innovations (Zhao et al., 2024). Furthermore, infrastructure limitations in rural settings, such as fewer charging stations and poorly maintained roads, pose practical challenges for EV adoption. Socioeconomic factors also play a significant role, as lower population density and longer travel distances make concerns about battery range and charging accessibility more pronounced. Rural residents may also have cultural preferences that emphasize self-reliance and traditional modes of transportation, making the adoption of EVs slower. The higher initial cost of EVs compared to conventional gasoline vehicles is another significant barrier in rural areas, where disposable income may be lower, and practical considerations often outweigh sustainability concerns (Koh and Yuen, 2023).

Individual differences such as age, technological experience, and cultural background play a crucial role in shaping pedestrian behaviour and preferences also toward autonomous vehicles. Faas and Baumann (2021) highlight that younger individual, often more adept with technology, are generally more receptive to eHMI cues compared to older pedestrians. Also, Lee et al. (2017) emphasised how from older people's perspective AVs are frequently associated with decreased safety and control. Older persons, who frequently have lower confidence in technology and are more sceptical of automation, are less likely to adopt fully automated systems. However, Abraham et.al (2017) also stated that, while older adults appear resistant to fully automated vehicles, they are more receptive to semi-automated in-vehicle technologies. This indicates that partial automation may act as a bridge to acceptance for older generations.

Research indicates that perceived usefulness, price, social support, lifestyle fit, and conceptual compatibility all have a significant impact on AVs acceptability across age groups. Furthermore, technological familiarity is strongly related to AV acceptability. Individuals with more experience and trust in new technologies are more likely to embrace self-driving cars, however these variables are usually inversely associated with age. Research is needed to explore the nuanced relationships between age, prior technology experience, perceived risks, and trust in AVs. Such studies could examine how these factors affect acceptance across varying levels of vehicular automation, from partially automated (AV3) to fully automated (AV5) systems (Lee et al., 2017; Abraham et al., 2017).

Furthermore, Abdullah and Sipos (2024) identified key factors, including age, gender, mobility habits, and driving license possession, that influence preferences for partially automated (AV3) and fully automated (AV5) vehicles. Older individuals, familiar with traditional driving practices, often prefer partially automated systems, whereas younger individuals exhibit greater openness to full automation. Gender differences also emerge, with men demonstrating a stronger preference for fully automated vehicles compared to women. Additionally, lifestyle factors, such as reliance on bicycles and frequent daily trips, align with a higher preference for AV5 systems, suggesting that automation could complement active transportation habits.

The acceptance of Autonomous Vehicles (AVs) among pedestrians is also closely tied to their neighbourhood of residence. Urban environments, with their dense traffic conditions and advanced infrastructure, create a setting where the potential benefits of AVs—such as accident reduction, optimized traffic flow, and parking alleviation—are more pronounced (Koh and Yuen, 2023). The higher frequency of road accidents in urban areas further underscores the appeal of AVs, which promise to enhance road safety through automation and real-time traffic management. Additionally, urban residents have greater exposure to AV pilot programs and testing initiatives, fostering familiarity and trust in the technology (Rahman and Thill, 2023). Urban infrastructure, including well-maintained roads, high-speed internet, and sophisticated traffic control systems, supports the effective operation of AVs. Urban populations are also generally more accustomed to technological advancements and innovation, making them more likely to adopt AV technology. These conditions make city dwellers more receptive to AVs as they perceive them as a viable solution to urban mobility challenges.

In contrast, rural areas pose significant obstacles to AV acceptance. With lower traffic congestion and fewer frequent road interactions, the immediate benefits of AVs, such as accident prevention and congestion management, may not seem as relevant. The lack of exposure to AV technology contributes to scepticism and distrust among rural residents, who may view AVs as unproven and less suited for unpredictable rural road conditions, including unpaved roads and adverse weather (Zhao et al., 2024).

Infrastructure limitations further complicate AV adoption in rural areas. Many rural roads are less maintained and lack the advanced traffic management systems necessary for AVs to function optimally. Wali and Khattak (2022) note that rural residents often question the reliability of AVs in these environments, particularly in terms of handling variable terrain and unexpected obstacles. Additionally, the slower rate of technological adoption in rural communities means that many residents may prioritize traditional, manually driven vehicles over autonomous options.

Overcoming these barriers will require targeted education and training strategies tailored to older adults' learning preferences. Educational tools, such as dealership demonstrations or online resources, can enhance understanding of system functionalities, reduce reliance on trial-and-error learning, and foster comfort with automation. Transparent and user-cantered design in EV and AV systems is equally critical to maintaining trust, as negative experiences can quickly undermine confidence and slow adoption.

3.3. The Role of Effective Communication on Safety and Trust

Pedestrians depend on non-verbal cues, like eye contact, gestures, and vehicle sounds, to cross streets safely. Electric vehicles complicate this by being quieter, benefiting noise reduction but increasing collision risk, especially for visually impaired individuals. Research shows artificial engine sounds improve EV detectability and trust. Meanwhile, autonomous vehicles lose vital driver–pedestrian communication cues; without eye contact or gestures, uncertainty at crosswalks can rise, prompting either hesitation or unsafe behaviour. Additionally, inattentional blindness (e.g., texting or listening to music) hinders pedestrians from noticing key signals, emphasizing the need for robust eHMIs that capture pedestrians' attention despite distractions.

Pedestrian decision-making is often characterized by assessing risks and uncertainties associated with crossing streets. The presence of AVs adds a layer of complexity to this decision-making process, as pedestrians must gauge the capabilities and intentions of a vehicle without a human driver. Studies by Faas and Baumann (2021) suggest that pedestrians use a combination of explicit and implicit (vehicle movement patterns) cues to make these assessments. However, inconsistencies in explicit signals design and functionality can lead to confusion, potentially increasing the risk of unsafe crossing behaviours.

To bridge these communication gaps, external Human-Machine Interfaces (eHMIs) have been proposed as a solution. These systems utilize visual, auditory, and occasionally haptic signals to communicate the vehicle's state, intent, and awareness of pedestrians, significantly improving the predictability of vehicle behaviour. Research has shown that well-designed eHMIs can enhance both trust and safety. For example, Faas et al. (2020) found that eHMIs providing clear signals, such as whether a vehicle is in autonomous mode or preparing to stop, lead to safer and more confident crossing decisions by pedestrians. These systems reduce the ambiguity of interactions and foster a greater sense of security in pedestrians (Hensch et al., 2020).

The type of information conveyed by eHMIs is crucial to their effectiveness. Studies suggest that minimalistic and intuitive signals, such as visual cues indicating a vehicle is stopping or yielding, are the most effective in fostering trust. Overly complex signals or displays that require interpretation risk overwhelming pedestrians and diminishing their confidence. Moreover, pedestrians show a clear preference for simple visual signals, as these are perceived as more intuitive compared to auditory or movement-based cues, which often require more active interpretation (Hensch et al., 2020; Faas et al., 2020).

The size of autonomous and electric vehicles plays a significant role in how pedestrians perceive safety and react emotionally. Larger vehicles tend to trigger stronger negative emotions, such as worry and stress, while also diminishing feelings of trust and security. This highlights the need for communication strategies that take vehicle size into account, as bigger vehicles can make pedestrians feel more vulnerable (Faas et al., 2020; Zhao et al., 2024).

Successfully integrating AVs and EVs into pedestrian environments requires thoughtful communication strategies to address the unique challenges these technologies present. External Human-Machine Interfaces have become essential in helping AVs communicate with pedestrians, while they may help in fostering adoption and acceptance of EVs, compensating for their near-silent nature.

3.3.1. Alternative Communication Technologies

Auditory and visual signals are not the only options that have been explored for communicating the intent of vehicles to pedestrians. Due to the limitations of traditional methods, such as the potential for auditory signals to contribute to noise pollution or visual cues being misinterpreted or missed in complex urban environments, researchers have increasingly focused on alternative methods for improving vehicle-pedestrians communication. These efforts are motivated by the need for systems that are more intuitive, effective, and capable of ensuring pedestrian safety in diverse traffic scenarios. Two such alternative approaches are bio-inspired communication methods and augmented reality (AR) interfaces, both of which offer unique ways to convey messages that traditional signals may fail to address adequately. By exploring these innovative systems, researchers aim to bridge the gap in vehicle-pedestrian interactions, enhancing both clarity and trust in autonomous technologies. Research so far has focused on experiments and studies focused on communication between autonomous vehicles and pedestrians, due to the lower maturity of this vehicles and the impossibility by pedestrians to rely on human contact and gestures.

The bio-inspired methodology, presented by Oudshoorn et al. (2021), sought to apply natural signalling mechanisms, using posture, gesture, and colour to communicate an AV's intentions. This approach was tested through an online crowdsourcing experiment involving 1,141 participants who viewed videos of an AV equipped with different eHMI systems approaching a crosswalk. The participants were tasked with pressing a key when they felt it was safe to cross and provided ratings on each eHMI's intuitiveness, clarity, and effectiveness. The bio-inspired eHMIs included a posture-based system (where the AV raises or lowers its body), a gesture-based system (with mechanical flaps signalling intent), and a colour-based system (changing colour to signal yielding or non-yielding behaviours). These systems were compared to more traditional lightbar and text-based eHMIs.

The findings indicated that the bio-inspired methods were generally less intuitive and effective than traditional visual systems. While the colour-based eHMI performed comparably to text displays in non-yielding scenarios, the posture and gesture systems were more difficult for pedestrians to interpret, likely due to their unfamiliarity in urban traffic settings. The effectiveness of the bio-inspired systems was identified through a combination of participant responses (e.g., when they pressed the key to signal crossing safety) and self-reported ratings, with traditional methods like lightbars receiving higher scores for both effectiveness and intuitiveness.

A second technology that has been investigated is the AR methodology explored by Tabone et al. (2023), which uses augmented reality interfaces to project virtual elements into the pedestrian's field of view, such as virtual crosswalks and stoplights. This study employed an online experiment with 992 participants from five European countries. The participants were shown nine different AR interfaces and asked to rate them based on factors such as clarity, intuitiveness, and aesthetic appeal. The AR designs ranged from simple projections of traditional traffic signals to more complex and immersive designs that introduced new communication methods.

The findings revealed that AR interfaces that mimicked traditional traffic signals, such as virtual stoplights or crosswalks, were rated as the most effective and intuitive. These AR interfaces were easy for pedestrians to understand because they built upon established visual conventions. On the other hand, more complex or abstract AR designs were found to be confusing or less clear, suggesting that AR's effectiveness depends heavily on maintaining familiarity with existing traffic communication methods. These findings were identified through participant ratings, which directly compared the clarity and usability of AR designs with their traditional counterparts.

When comparing bio-inspired and AR methods with traditional visual (e.g., light and text displays) and auditory signals (e.g., beeping or spoken commands), several key differences in methodology and effectiveness emerge.

- Visual methods, such as lightbar and text-based eHMIs, are already well-established in traffic systems and they remain the most effective and intuitive methods due to their wide recognition. For example, red and green lights are universally understood, and text displays like "Walk" or "Don't Walk" are unambiguous. In both studies, these traditional systems consistently received the highest ratings for intuitiveness and effectiveness. Pedestrians can quickly and accurately interpret these signals without the need for additional training.
- Traditional auditory signals, such as beeping or voice commands, can be effective in attracting attention, especially in noisy or visually distracting environments. However, these signals may not always be effective for all users, such as those with hearing impairments, and can contribute to noise pollution in urban areas. While neither study focused specifically on auditory signals, the lack of auditory feedback in both bio-inspired and AR methods highlights a potential limitation, as visual signals alone may not always be sufficient in complex environments.

Both methodologies (bio-inspired communication and AR) offer alternative approaches to traditional visual and auditory systems, but they face challenges in terms of intuitiveness and effectiveness. Traditional visual cues, like lightbars and text displays, remain the most reliable and intuitive methods for signalling AV intent, while auditory signals play an important, albeit sometimes limited, role in enhancing awareness. Bio-inspired methods, particularly those involving colour changes, show potential but generally require more refinement. AR interfaces, when designed to mirror familiar traffic systems, can be just as effective as traditional methods but risk losing clarity when introducing complex or unfamiliar designs.

4. Research Design and Methodology

4.1. Hypothesis

In this research, the communication between pedestrians and EVs or AVs has been analysed separately, and specific hypothesis have been developed for each vehicle concept. However, the majority of the hypotheses attempt to study the same factors in order to perform cross-comparison of the results for EVs and AVs. Table 3 shows the hypothesis that will be tested through the analysis for each vehicle concept.

Hypothesis N°	Electric Vehicles	Autonomous Vehicles
1	*People who don't perceive the low-level noise as a safety issue will perceive auditory signals as the least effective*	*People who don't think of crossing in front an AV as a danger, will show lower level of perceived effectiveness all signals' categories (visuals, auditory and movement-based) compared to those who think of it as a safety issue*
2	*Different age clusters will show different preferences for the signals categories (visuals, auditory and movement-based)*	*Favourite mean of transportation affects preferences for the signals categories (visuals, auditory and movement-based)*
3	*Neighbourhood of residence affects preferences for the signals categories (visuals, auditory and movement-based)*	*Pedestrians who possess a driver's license will report higher levels of understanding (less Confusion) and trust in AV compared to those without a driver's license.*
4	*Pedestrians who are also experienced drivers are likely to trust Electric Vehicles more, reporting higher level of Trust and Safety when crossing in front of them compared to non-drivers.*	*Different age clusters will show different preferences for the signals categories (visuals, auditory and movement-based)*
5	*Pedestrians with higher study degree are more likely to show more confidence (higher values of Trust and Safety) towards EV*	*Neighbourhood of residence affects preferences for the signals categories (visuals, auditory and movement-based)*
6	*Favourite mean of transportation affects preferences for the signals categories (visuals, auditory and movement-based)*	*Female pedestrians will report lower levels of perceived safety and trust (and consequently higher in worry and stress) in interactions with AVs compared to male pedestrians.*

7	*As the size of the vehicle increases, so increase intensity levels for negative emotions (Worry, Stress, Confusion, Fear).*	*Pedestrians with higher study degree are more likely to show more confidence (higher values of Trust and Safety) towards AV*
8	*Prior experience of pedestrians with EV has an effect on their trust. Those with experience onboard will show highest scores in positive emotions (Trust and Safety)*	*Pedestrians with prior experience or interaction with AVs will report higher levels of perceived safety and trust when interacting with AVs compared to those with no prior experience.*
9	*Implementation of signals (visual, acoustic and Movement based) is positively correlated with positive emotions (Trust, Safety, Adrenaline) and negatively correlated with negative emotions (Fear, Stress, Worry, Confusion)*	*As the size of the vehicle increases, so increase intensity levels for negative emotions (Worry, Stress, Confusion, Fear).*
10	*Those who perceive crossing in front of an EV as a threat are more likely to consider the low noise of EV's as a danger*	*Implementation of signals (visual, acoustic and Movement based) is positively correlated with positive emotions (Trust, Safety, Adrenaline) and negatively correlated with negative emotions (Fear, Stress, Worry, Confusion)*
11	*People who don't think of crossing in front an EV as a danger, will show lower level of perceived effectiveness all signals' categories (visuals, auditory and movement-based) compared to those who think of it as a safety issue*	

Table 3

4.2. Design of the questionnaires

Separate questionnaires for AVs and EVs were designed to capture pedestrian perceptions of three key signal categories (Visual, Acoustic and Movement-based) and their emotional responses. Demographic variables, prior experiences with EVs and AVs, and contextual factors, such as vehicle size, are analysed to understand their influence on perceived signal effectiveness and emotional intensity. The two surveys have the same structure, as follows:

Section 1: Demographic information *(Age, Gender, Study Degree, Driver license ownership, Most frequent mean of transport, Neighbourhood)*

Section 2: Investigation preferences regarding communication methods between EV/AV and pedestrians. In this section we have gathered data regarding:

- **Perceived effectiveness** of three signals *(Visual, Acoustic, Movement-based),* measured with a Likert Scale from 1 to 5
- **Emotion intensity** when crossing in front of an EV/AV *(Worry, Trust, Indifference, Stress, Fear, Safety, Adrenaline, Confusion),* measured with a Likert Scale from 1 to 5
- **Preferred method of communication** for each signal category (multiple responses were allowed).
- **Prior experience** with EV/AV as drivers, passengers, or pedestrians, in order to understand the correlation between perceived effectiveness of signals and emotional response.
- The impact of **vehicle size**, to understand its role in shaping emotional responses, particularly fear, stress, and safety perception.

The major focus of the questionnaires is to assess the perceived utility and effectiveness of various eHMIs designed to communicate an EV or AV's actions and intentions to pedestrians. As mentioned, three distinct signal categories are explored: visual signals, auditory signals and movement-based signals. These categories include both traditional and innovative methods, providing a comprehensive evaluation of pedestrian preferences. Participants were asked to rate the effectiveness of each category and select their preferred methodologies within these groups. This approach aims to highlight which signals are deemed most useful but also reveal whether certain designs may align better with specific characteristics of pedestrians.

4.2.2. Design of Experiment - EV

The sample size for this study has been set at a minimum of 180 participants. This threshold aligns with similar university studies that have employed comparable sample sizes to ensure statistical validity. The sample is designed to maintain an equal gender distribution (50% male, 50% female) to mitigate gender-related biases in perception and decision-making processes concerning vehicle interaction. Participants must be at least 16 years old, as individuals in this age group and older are more likely to engage independently in pedestrian activities, making their insights more relevant to real-world interactions. Furthermore, participants must be of Italian nationality. No constraints are imposed regarding participants' professional or academic backgrounds, allowing for a diverse range of perspectives that reflect varying levels of familiarity with technological advancements in mobility. However, participants must reside in urban areas with populations exceeding 50,000 inhabitants. This criterion is justified by the fact that EVs are primarily introduced and tested in urban environments where pedestrian-vehicle interactions are more frequent and complex. These constraints have been imposed to have a sample representative of the population. The questionnaire is distributed via multiple online channels, including LinkedIn, Instagram, WhatsApp, Telegram, and Facebook.

4.2.3. Design of Experiment – AV

For the same reasons mentioned for the EV sample, the study targets a sample size of at least 180 participants, with a gender distribution of 40% male and 60% female. A higher proportion of female participants has been included, as existing literature suggests that women tend to be more hesitant toward AVs. The minimum age requirement is 16 years, with at least 10% of respondents being over 60 years old, since previous research indicates that individuals above this age tend to be more sceptical about AVs. The study includes participants from various nationalities, since reducing the location to Italy would have been a limitation due to the low diffusion of AV in the country. Specifically, sample includes European (excluding Italians, with a focus on German, English, and French respondents), Asian (mainly Chinese, Japanese, and Indian), and American participants. These countries were selected based on the diffusion rate of AVs in their specific continents, ensuring that respondents are more likely to have encountered these vehicles. There are no restrictions regarding professional or academic background in order to grant wider representation of individuals; however, all participants must reside in urban areas with populations exceeding 50,000 inhabitants since, as for EVs, urban environments is where is more likely to encounter AVs. Same channels have been used: the questionnaire is distributed through multiple online platforms, including LinkedIn, Instagram, WhatsApp, Telegram, and Facebook, ensuring broad accessibility and engagement.

4.3. Performed Analysis

After the data collection, the datasets have been codified in order to conduct statistical analysis.

Then, descriptive and statistical analysis are performed to investigate the correlation between the variables. In the following section the analysis delves into each hypothesis punctually. The process used to verify the hypothesis is composed by these steps:

1. Descriptive analysis, by analysing the graphs showing the values of the dependent variable, clustered by independent variables in order to detect possible differences between groups and determine preliminary insights
2. Statistical test to check the correlation between the independent and dependent variables. Following rules explain the rationales for the employment of statistical tests:
    a. Kruskal-Wallis Test is employed when investigating correlation between categorical and Likert scale variables. When necessary, it has been used also the Dunn's Test as post-hoc.
    b. Chi-squared Test employed when investigating correlation between binary and/or categorical variables
    c. Logistic Linear Regression when investigating correlation between variables on Likert scale.
    d. Wilcoxon Test when making comparisons between responses on the same variables but in different conditions.
    e. Kendall's Tau when investigating ordinal and nominal relationship between variables on Likert scale.

Table 4 illustrates the statistical analysis performed for each variable explored in both the questionnaires *(the variables marked with "*" have been considered for the EV analysis exclusively)*. Based on results of the appropriate test, determination of the outcome (Hypothesis Supported/Not Supported).

Statistical Test	Independent variable	Dependent variable
Kruskal-Wallis	• Age • Means of transport • Neighbourhood • Perception of danger when crossing	• Effectiveness of signal categories
	• Study Degree • Perception of danger when crossing	• Emotional responses
Chi-squared	• Age • Means of transport • Neighbourhood	• Choice of the preferred method of communication
	• Perception of danger when crossing	• Low noise perception* • Effectiveness of signal categories
Logistic Linear Regression	• Prior experience • Driver license ownership	• Emotional Responses
	• Low noise perception*	• Effectiveness of signal categories*
Wilcoxon	• Size of the vehicle	• Emotional responses
Kendall's Tau	• Effectiveness of signal categories	• Emotional responses

Table 4

5. Findings and insights

5.1. Electric Vehicles

To provide a descriptive explanation of the sample involved in the research, the analysis will start by showing the distribution of the demographic variables. The key variables include:

- Age (In years)
- Gender
- Study Degree
- Neighbourhood of residence
- Ownership of a driver's license
- Most frequent means of transportation used

5.1.1. Sample Description

This section aims to provide a descriptive overview of the sample involved in the EVs research.

For the EV survey, 187 responses have been gathered. An operation of data cleaning has been done, resulting in 8 responses due to the lack of logical correctness, meaning that analysis has been done using 179 responses. The survey has been distributed exclusively among Italian participants

The charts below show graphically the distribution of each of the key demographic variables.

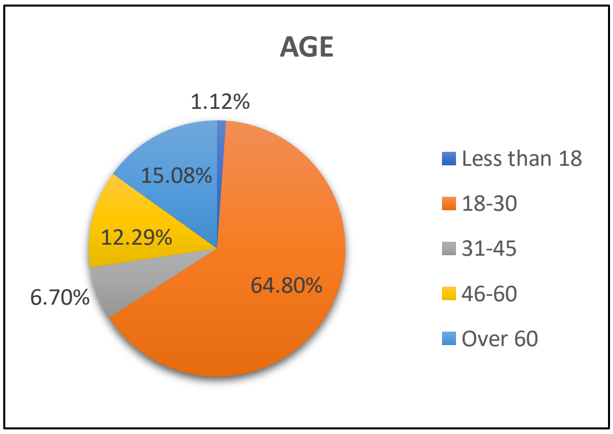


Figure 4 – Percentage of participants based on age clusters

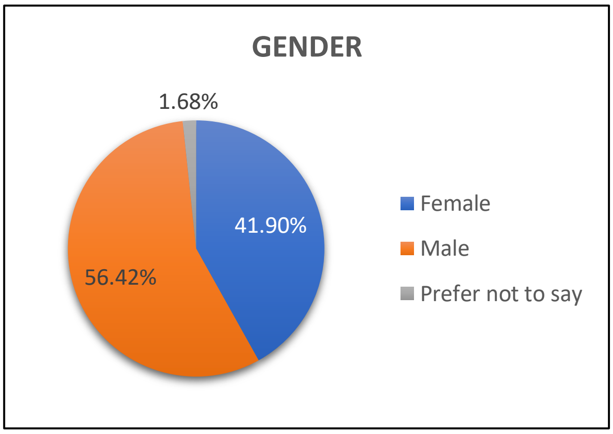


Figure 5 – Percentage of participants based on gender

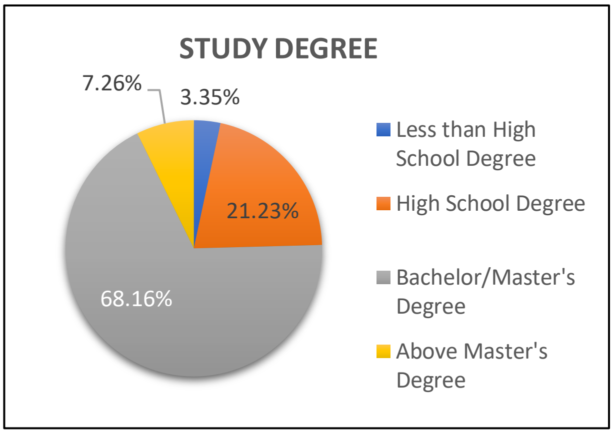


Figure 6 – Percentage of participants based on study degree

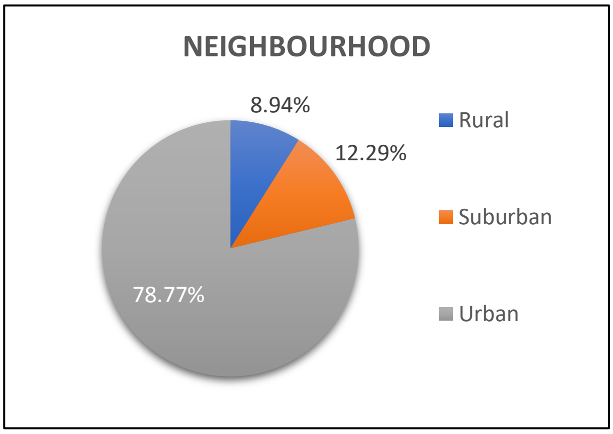


Figure 7 – Percentage of participants based on neighbourhood of residence

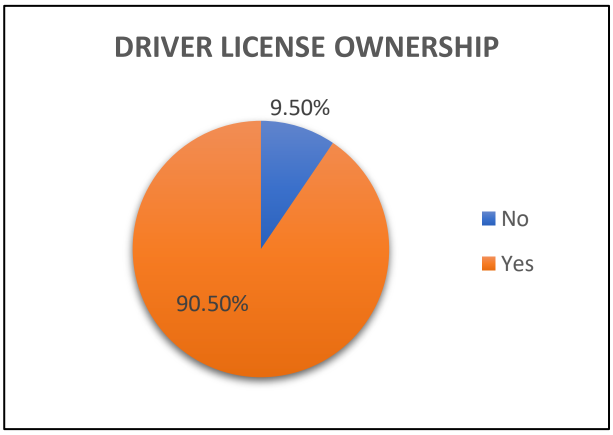


Figure 8 - Percentage of participants based on driver license ownership

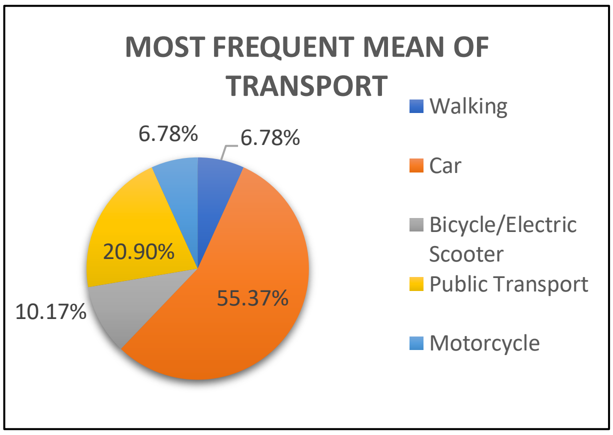


Figure 9 - Percentage of participants based on transport habits

It is important to provide a comparison with the Italian population in order to understand the degree of representation of the sample. Tables 5, 6, 7 and 8 below show the percentages for the distribution of four demographic variables, specifically *Age (Table 5), Gender (Table 6), Study Degree (Table 7) and Driver License Ownership (Table 8).*

Age	**Italian Population**	**Sample**	**Notes**
Less than 18	16,8%	1,1%	The sample over represents the age group 18-30. Individuals with less than 18 years are not represented because not in the scope of the analysis.
18-30	13,8%	64,8%	
31-45	22,6%	6,7%	
46-60	20,8%	12,3%	
Over 60	25,9%	15,1%	

Table 5 – Comparison between sample and Italian population for age clusters

Gender	Italian Population	Sample	Notes
Male	48,4%	56,4%	The sample is representative of the Italian population. The missing 1,7% in the sample is due to respondents who did not disclose their gender
Female	51,6%	41,9%	

Table 6- Comparison between sample and Italian population for gender

Study Degree	Italian Population	Sample	Notes
Less than High School Diploma	58.5%	3,4%	A larger proportion of the sample has a university-level education or higher. Under-representation of people with low educational qualifications may be due to the exclusion of individuals younger than 18 from the scope of the analysis. This may result in a bias the results towards greater acceptance or understanding of new vehicle technologies.
High School Diploma	30,1%	21,2%	
Bachelor/master's Degree	11,1%	68,2%	
Higher than master's degree	0,3%	7,3%	

Table 7 - Comparison between sample and Italian population for study degree

Driver License Ownership	Italian Population	Sample	Notes
Yes	65,1%	90,5%	The sample under-represents people without a driving license. Excluding individuals with less than 18 years old from the scope of the analysis may have contributed to this under representation.
No	34,9%	9,5%	

Table 8 - Comparison between sample and Italian population for driver license ownership

5.1.2. Findings

Each of the hypotheses will be tested according to the methodology described before. This section aims to delve into a punctual analysis of the hypothesis in order to gather the findings and draw conclusions about the perception and emotional responses of pedestrians when interacting with EVs.

H1: People who don't perceive the low-level noise as a safety issue will perceive auditory signals as the least effective

- *Method: Logistic Linear Regression*
- *Outcome: Not Supported*

Data concerning pedestrians' perception of low noise as a potential hazard were collected through Question 8 of the survey. Figure 10 presents the average scores of perceived effectiveness for each signal category, based on respondents' views regarding the low noise of EVs as a danger. Across all clusters, individuals who perceive low noise as a threat generally attribute higher effectiveness scores to the signals, indicating a perception that these signals are more useful. However, no significant differences can be noticed between these clusters by observing the chart.

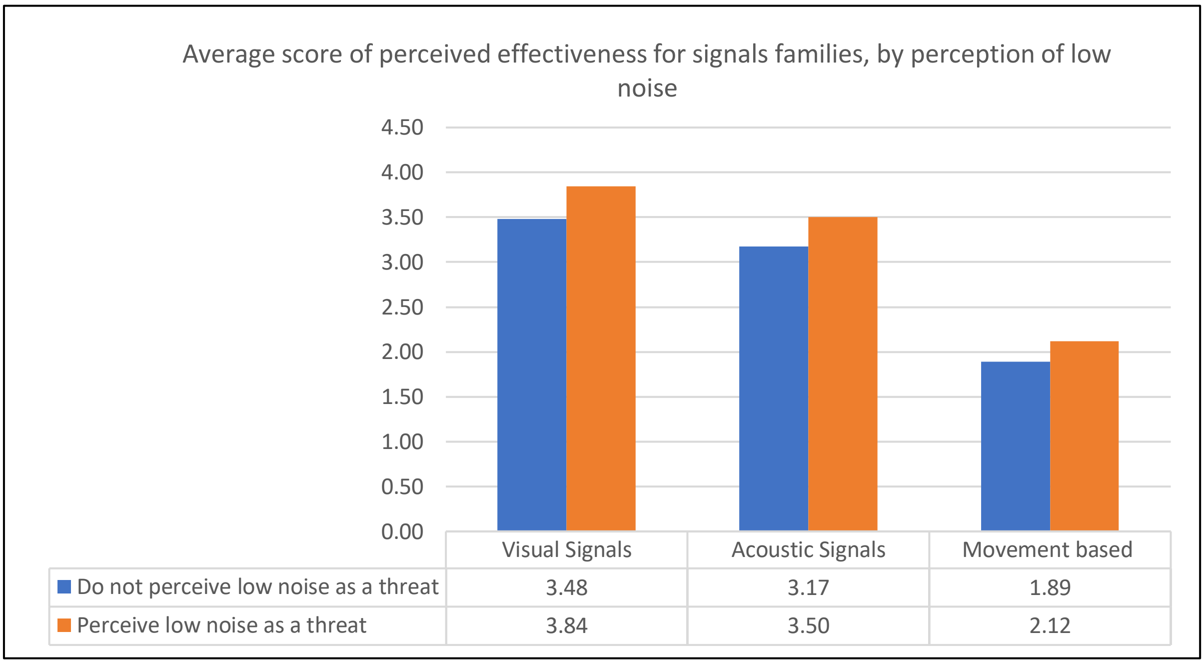


Figure 10

To examine the relationship between a Likert-scale variable (perceived effectiveness) and a categorical variable (perception of low noise as dangerous), logistic linear regression was employed. The results, summarized in *Table 9*, indicate a positive correlation for all signal categories, suggesting that those who perceive low noise as a hazard tend to rate the signals as more effective. Nonetheless, the p-values for all categories exceeded 0.05, demonstrating that the observed correlation is weak and lacks statistical significance.

Categories	**Value**	**P-value**
Visual Signals	0,56	0,07
Acoustic Signals	0,49	0,11
Movement Based Signals	0,5	0,12

Table 9 – Results of a logistic linear regression between low noise perception and signals categories

The hypothesis must be rejected, the perception of the noise of EV does not influence the effectiveness perceived of signals.

H2: Different age clusters will show different preferences for the signals categories (visuals, auditory and movement-based)

- *Method: Kruskal-Wallis, Chi-Squared*
- *Outcome: Not Supported*

Figure 11 shows the average score for the different signals' families, divided by age cluster:

Visual signals are those perceived with highest effectiveness for every age cluster, slightly higher than acoustics. Movement based signals are those with the lowest perceived effectiveness for each age cluster. From the chart there is no particular difference in trends among clusters than can be noticed.

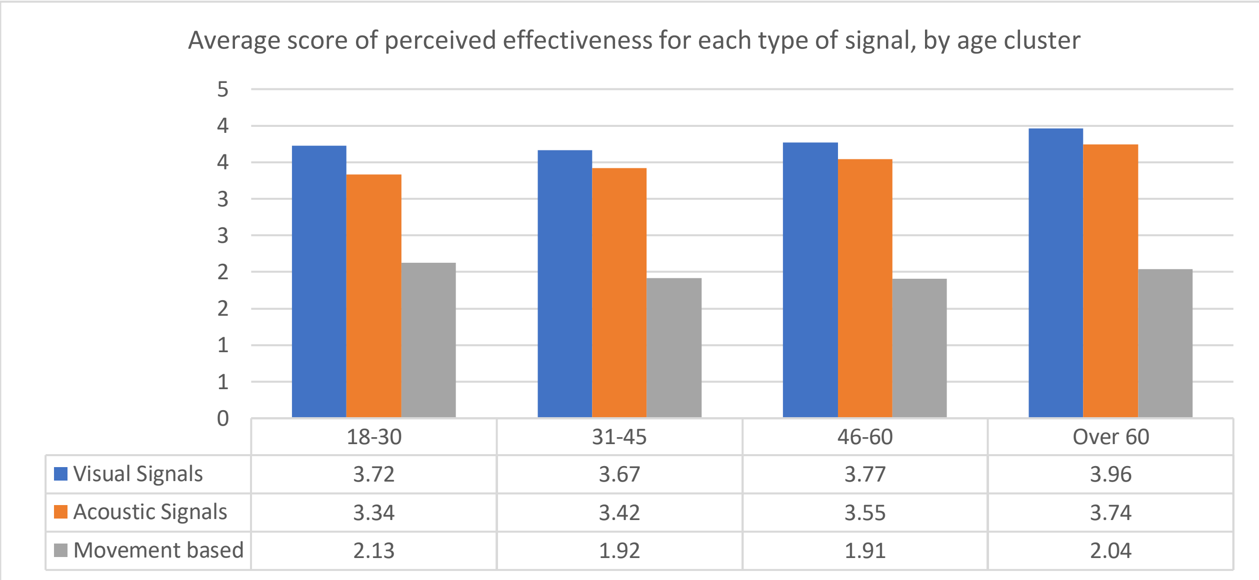


Figure 11

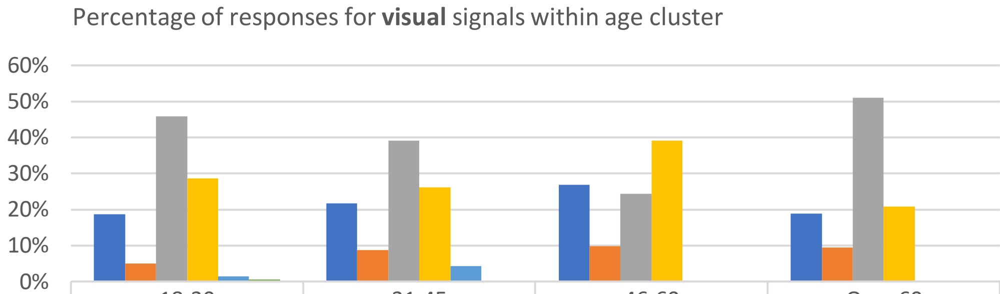
To test the correlation of a variable on a Likert scale between groups, a Kruskal-Wallis test has been employed. However, the results confirm the impression of no statistical correlation between the variables (*Table 10*).

Categories	**Chi-Squared**	**P-value**
Visual Signals	3,58	0,47
Acoustic Signals	4,24	0,38
Movement based Signals	3,01	0,56

Table 10 – Results of the Kruskal-Wallis test between age clusters and signal categories

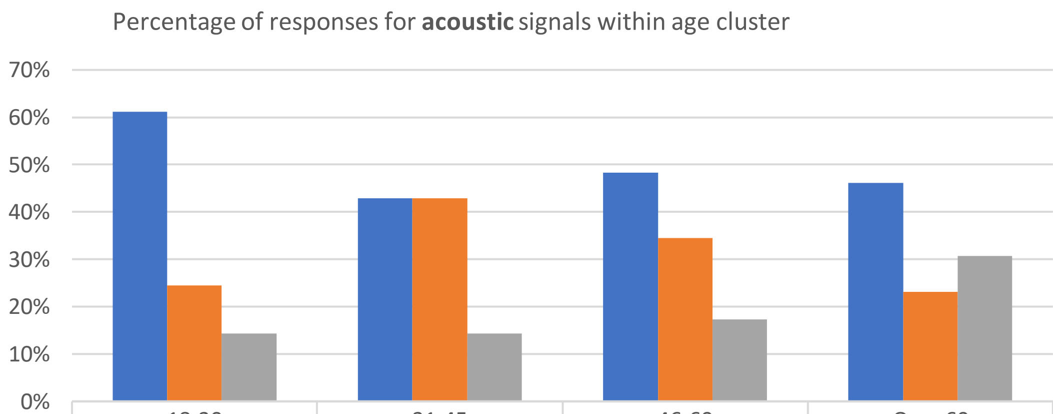
Additional Analysis

To go further in the analysis, it has been deemed appropriate to investigate the possible differences among age clusters on the choice of favourite signal methodology. The charts below show the percentage of responses for visual (Figure 11), acoustic (Figure 12) and Movement-based (Figure 13) signals within age cluster.



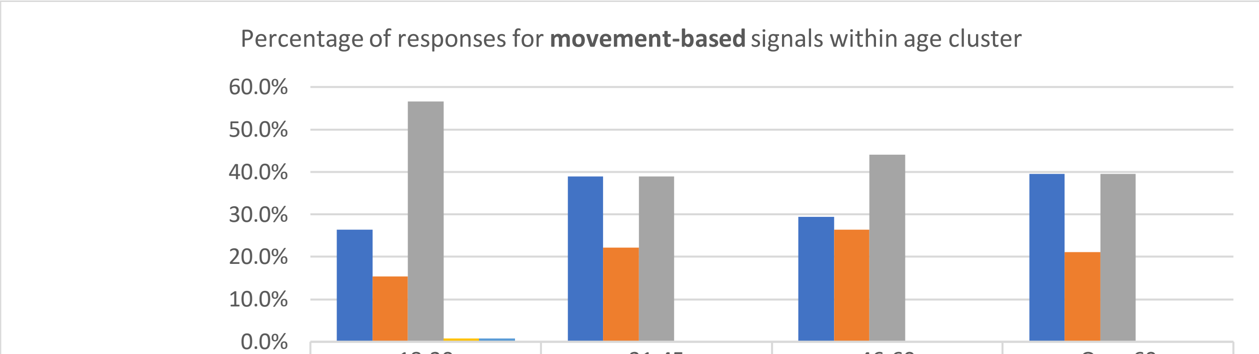
	18-30	31-45	46-60	Over 60
Images	19%	22%	27%	19%
Text	5%	9%	10%	9%
Colours	46%	39%	24%	51%
Ground Projections	29%	26%	39%	21%
Eye contact with driver	1%	4%	0%	0%
Turn signals	0%	0%	0%	0%

Figure 11



	18-30	31-45	46-60	Over 60
Warning Sounds	61%	43%	48%	46%
Spoken Messages	24%	43%	34%	23%
Musical Tones	14%	14%	17%	31%

Figure 12



	18-30	31-45	46-60	Over 60
Rearview Mirrors	26.5%	38.9%	29.4%	39.5%
Chassis Movement	15.4%	22.2%	26.5%	21.1%
Appendages	56.6%	38.9%	44.1%	39.5%
Turn Signals	0.7%	0.0%	0.0%	0.0%
Colour inside front light	0.7%	0.0%	0.0%	0.0%

Figure 13

Visual signals: For visual signals *"Colours"* is by far the favourite methodology by respondents.

Figure 11 does not show any significant differences in trends between clusters, except for the methodology *Ground Projections,* which have more popularity among participants of age between 46-60. To investigate the statistical correlation between the variables, when dealing with binary variables the most suitable test is the Chi-squared. *Table 11* shows the results of the test.

Visual	Images	Text	Colours	Projections on the ground	Eye-contact with driver	Turn signals
Chi-squared Value	3,7	3,72	22,66	5,34	3,27	0,55
P-value	0,45	0,45	0,15e-03	0,25	0,51	0,97

Table 11 – Results of the chi-squared test between age clusters and visual signals

The results confirm the first impression, among visual signals, age seems to be correlated with the choice of "Colours" as methodology. It is necessary to read the residual values (*Table 12*) to delve into how age clusters influence the variable.

Colours	No	Yes
18-30	-0,33	0,17
31-45	0,28	-0,15
46-60	3,39	-1,76
Over 60	-2,39	1,24

Table 12 – Residual values for "Colours"

The 46-60 age group shows a significant tendency to not choose *"Colours"* (positive residual for 0) compared to other groups, while over 60 age group is less likely to not choose *"Colours"* (negative residual for 0) and shows a moderate tendency to choose it.

For the remaining age groups, the residuals are close to zero, suggesting no significant deviation from the expected patterns of behaviour.

Acoustic Signals: From Figure 12 it can be noticed that, across all age clusters, "Warning Sounds" are the most preferred acoustic methodology. However, preference decreases with age. The "Musical Tones" category shows a clear upward trend with age. This suggests that older individuals may find musical tones more intuitive or less intrusive compared to younger age groups. A peak in the preference for "Spoken Messages" is observed in the 31-45 age group, where it ties with Warning Sounds. This preference declines in both younger (24%) and older groups (23%), indicating a middle-age preference for verbal communication.

Results of Chi-squared test (*Table* 13) indicate a correlation with the choice of *"Musical Tones".*

Acoustic	Warning Sound	Musical Tones	Spoken Messages
Chi-squared Value	6,66	9,70	4,14
P-value	0,16	0,046	0,39

Table 13 - Results of the chi-squared test between age clusters and acoustic signals

By looking at residual values (*Table 14*), it can be noticed that the Over 60 age group shows a significant preference for musical tones, as indicated by the large positive residual for 1, while other age groups do not show any significant deviation in their choices, with residuals close to zero. Finally, the 46-60 age group aligns almost perfectly with the expected behaviour, showing no meaningful deviation in either choice.

Musical Tones	No	Yes
18-30	0,59	-1,08
31-45	0,25	-0,54
46-60	0,01	-0,02
Over 60	-1,28	2,34

Table 14 – Residual values for "Musical Tones"

Movement-based signals: Figure 13 clearly indicates "Appendages" as the most preferred in the 18-30 age group, showing a strong preference compared to other movement-based signals. However, this preference declines significantly in older age clusters. This suggests younger pedestrians may find dynamic, noticeable features like appendages more intuitive. The preference for "Rearview Mirrors" steadily increases across age clusters. Turn Signals and Colour inside the front light were nearly non-existent across all age groups, with percentages close to 0%.

However, the Chi-squared test (*Table 15*) shows that the choice of these signals is not correlated with age.

Movement based	Rearview Movement	Chassis Movement	Appendages Movement	Turn Signals	Colour in the front lights
Chi-squared Value	8,60	7,42	1,63	0,55	0,55
P-value	0,072	0,12	0,80	0,97	0,97

Table 15 - Results of the chi-squared test between age clusters and movement-based signals

Hypothesis 3: Neighbourhood of residence affects preferences for the signals categories (visuals, auditory and movement-based)

- *Method: Kruskal-Wallis, Chi-Squared*
- *Outcome: Not Supported*

Figure 14 shows the average score for the different signals' families, divided by neighbourhood. The hierarchy is the same as previous clusters: Visual signals are those with the highest perceived effectiveness, followed by acoustic and last the movement-based. No particular correlation can be detected from the chart.

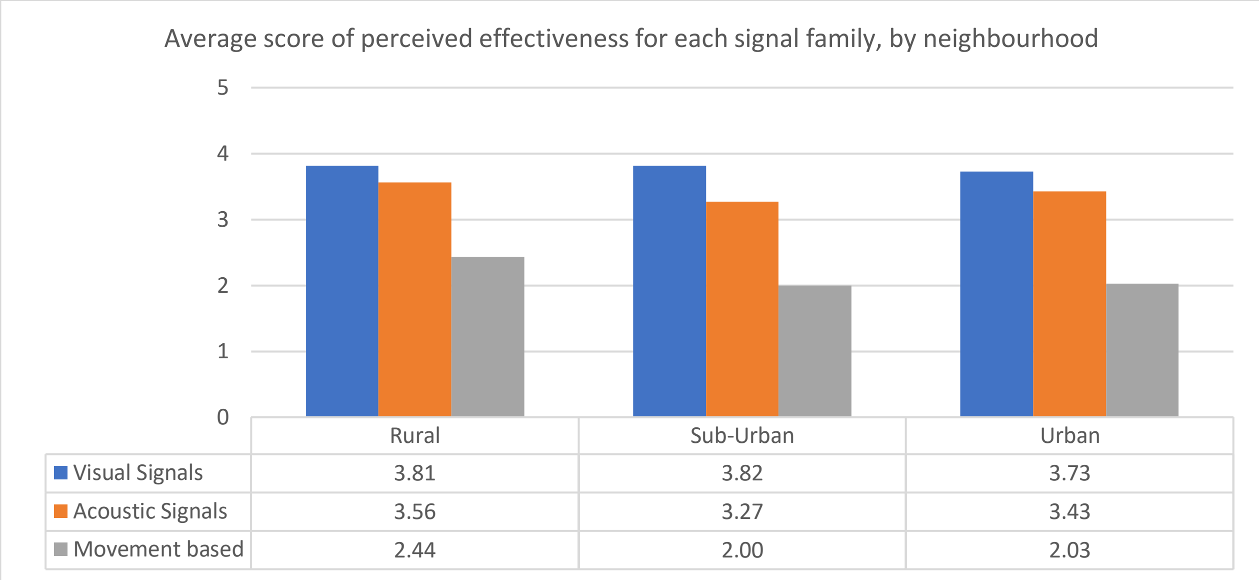


Figure 14

Results of the Kruskal-Wallis test confirm the impression, neighbourhood of residence cannot be proven to be correlated with the perceived effectiveness of signals' families.

Additional Analysis

To go further in the analysis, we have investigated also the presence of possible correlation between the neighbourhood of residence and choice of signal methodology (*Table 16-17-18*). However, after the chi-squared test, results clearly indicate the absence of correlation between neighbourhood of residence and the choice of the favourite signal methodology.

VISUAL	**Images**	**Text**	**Colours**	**Projections on the ground**	**Eye-contact with driver**	**Turn signals**
Chi-squared Value	3,68	0,17	0,99	0,46	1,10	0,27
P-value	0,16	0,92	0,61	0,80	0,58	0,87

Table 16 – Results of a chi-squared test between neighbourhood of residence and visual signals

ACOUSTIC	**Warning Sound**	**Musical Tones**	**Spoken Messages**
Chi-squared Value	1,506	0,044	1,417
P-value	0,471	0,978	0,492

Table 17 – Results of a chi-squared test between neighbourhood of residence and acoustic signals

MOVEMENT BASED	Rearview Movement	Chassis Movement	Appendages Movement	Turn Signals	Colour in the front lights
Chi-squared Value	1,391	0,685	1,071	0,271	0,271
P-value	0,499	0,71	0,586	0,873	0,873

Table 18 – Results of a chi-squared test between neighbourhood of residence and movement-based signals

H4: Pedestrians who are also experienced drivers are likely to trust Electric Vehicles more, reporting higher level of Trust and Safety when crossing in front of them compared to non-drivers.

- *Method: Logistic Linear Regression*
- *Outcome: Not Supported*

The hypothesis aims to investigate if the ownership of a driver license may affect the emotional response of pedestrians when approaching an EV. According to literature, drivers are less intimidated due to their knowledge of road dynamics, while people who don't know how to drive may show higher diffidence. Figure 15 shows the average scores for each emotion perception, by ownership of driver license

Contrary to expectations, for *Stress, Fear, Worry* people who owns a driver license present higher scores. However, they are quite low compared to those of positive and neutral emotions (Trust, Safety, Indifference). For the latter emotions, the trend is the opposite: people with a driver license have lower score compared to those who do not possess one. It can be noticed that the differences between clusters are minimal, suggesting absence of correlation.

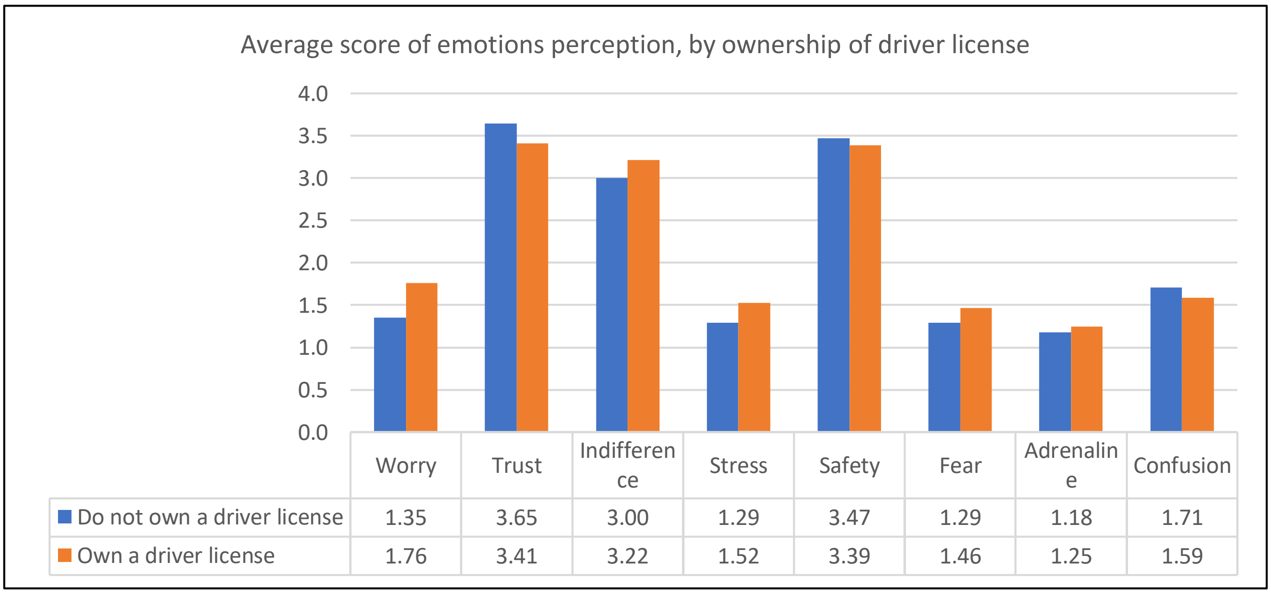


Figure 15

To check on statistic correlation, a logistic linear regression has been performed. *Table 19* shows that there is no correlation between not only Trust and Safety, but also for the other emotions. The hypothesis has to be rejected, ownership of a driver license does not have an effect on emotions

	Value	P-value
Worry	0,94	0,09
Trust	-0,29	0,52
Indifference	0,25	0,58
Stress	0,26	0,63
Safety	-0,13	0,77
Fear	0,26	0,64
Adrenaline	0,31	0,69
Confusion	-0,24	0,64

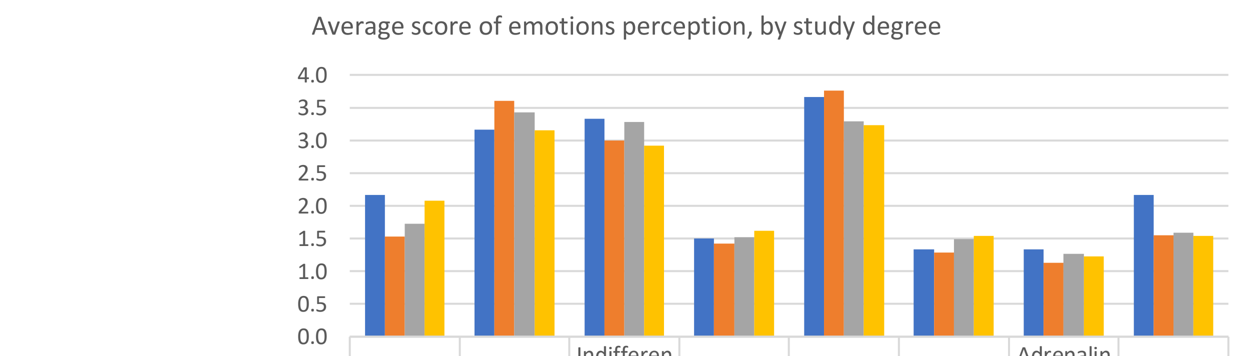
Table 19 – Results of a logistic linear regression between driver license ownership and emotional responses

H5: Pedestrians with higher study degree are more likely to show more confidence (higher values of Trust and Safety) towards EV

- *Method: Kruskal-Wallis*
- *Outcome: Not Supported*

Figure below shows the average scores for emotions perception, divided by study degree. By looking at figure 16, it can be noticed that higher education levels are associated with lower trust and safety perception, higher stress and fear, and reduced indifference, indicating greater engagement but also higher caution. In contrast, lower education levels show higher worry, confusion, and indifference, reflecting greater uncertainty and disengagement.

However, differences between clusters are minimal, indicating probably absence of correlation.



	Worry	Trust	Indifferen ce	Stress	Safety	Fear	Adrenalin e	Confusion
Inferior to High Scool	2.17	3.17	3.33	1.50	3.67	1.33	1.33	2.17
High Scool Diploma	1.53	3.61	3.00	1.42	3.76	1.29	1.13	1.55
Bachelor's/Master's Degree	1.72	3.43	3.28	1.52	3.29	1.49	1.27	1.59
Superior to Master's Degree	2.08	3.15	2.92	1.62	3.23	1.54	1.23	1.54

Figure 16

To check on correlation a Kruskal-Wallis test has been performed. Based on the results in *Table 20*, the impression seems correct: study degree cannot be proven to influence the intensity of emotions perception.

	Value	P-value
Worry	5,95	0,11
Trust	2,05	0,56
Indifference	1,79	0,61
Stress	1,57	0,67
Safety	5,67	0,13
Fear	2,82	0,47
Adrenaline	1,55	0,67
Confusion	2,68	0,44

Table 20 – Results of Kruskal-Wallis test between study degree and emotional responses

Hypothesis 6: Favourite mean of transportation affects preferences for the signals categories (visuals, auditory and movement-based)

Method: Kruskal-Wallis

Outcome: Supported

Figure 17 presents the average score for the different signals' families, divided by the most frequent means of transport. It can be noticed that all clusters show similar scores for all signal signals. The only cluster that deviates from others is *"Walking"*, which shows higher values for visual and movement-based signals.

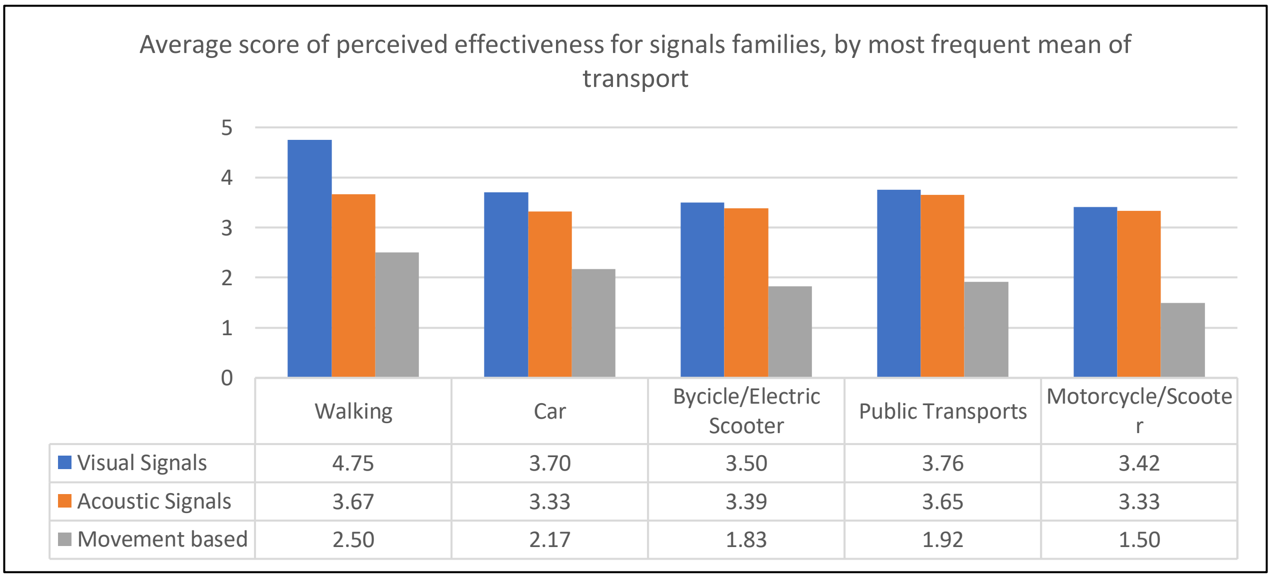


Figure 17

The results of the Kruskal-Wallis test (*Table 21*) prove the presence of a correlation between most frequent means of transportation and visual signals (p-value <0,05)

Categories	Chi-value	P-value
Visual Signals	13,44	0,037
Acoustic Signals	2,86	0,82
Movement based Signals	12,02	0,06

Table 21 – Results of the Kruskal-Wallis test between transport habits and signal categories

The post-hoc Dunn's is used to have a better understanding of the differences between groups for visual signals. Results reveals that there is a significant difference between participants who usually walk compared to those who uses a car, indicating the latter as perceiving these signals less effective (Z value is >0). *Table 22* shows only the results that have been proven to be significant.

Comparison	Z	P unadj.	P adj
Walking - Car	3,09	0,20e-02	0,04

Table 22 - Results of the Dunn's Test for visual signals

Additional Analysis

It was deemed appropriate to investigate also if the means of transportation has an influence on the choice of a favourite methodology for each signal category. The tables below show the results of the Chi-squared test. They suggest the presence of correlation with *"Spoken Messages"* (*Table 24*) and *"Rearview Movements"* (*Table 25*), while it appears there is no correlation with any of the visual signals (*Table 23*).

Visual	Images	Text	Colours	Projections on the ground	Eye-contact with driver	Turn signals
Chi-squared Value	10,646	3,226	2,56	5,388	12,87	3,859
P-value	0,1	0,767	0,8167	0,495	0,0451	0,6957

Table 23 – Results of chi-squared test between transport habits and visual signals' signals. The method "Eye-contact with the driver" is not considered due to the very low number of respondents who indicated it as a choice.

Acoustic	Warning Sound	Musical Tones	Spoken Messages
Chi-squared Value	6,40	6,49	14,45
P-value	0,38	0,37	0,02

Table 24 – Results of chi-squared test between transport habits and acoustic signals' signals

Movement based	Rearview Movement	Chassis Movement	Appendages Movement	Turn Signals	Colour in the front lights
Chi-squared Value	12,95	2,73	5,07	3,86	0,83
P-value	0,04	0,84	0,53	0,69	0,99

Table 25 - Results of chi-squared test between transport habits and movement-based signals' signals

By looking at the residual values (*Table 26-27*) is possible to understand the type of correlation that binds the variables.

Spoken Messages	No	Yes
Walking	-0,68	0,95
Car	0,92	-1,28
Bicycle/ electric scooter	-1,41	1,96
Public transports	-0,48	0,67
Motorcycle/scooter	0,74	-1,03

Table 26 – Residual values for "Spoken Messages"

Rearview Movement	No	Yes
Walking	0,60	-0,76
Car	-1,06	1,34
Bicycle/ electric scooter	0,28	-0,36
Public transports	1,52	-1,92
Motorcycle/scooter	-0,51	0,64

Table 27 – Residual values for "Rearview Movements"

- The *“Bicycle/electric scooter”* group shows a potential tendency towards more "Yes" responses (residual = 1.9647). All other transportation modes show deviations that are small and not meaningful
- The results do not show any statistically significant deviations. However, the Public Transport group displays a notable pattern. It is close to being over-represented in "No" responses and under-represented in "Yes" responses for "Rearview Movement."

H7: As the size of the vehicle increases, so increase intensity levels for negative emotions (Worry, Stress, Confusion, Fear).

Method: Wilcoxon-Test

Outcome: Supported

Figure 18 shows the difference in average of the scores for the intensity of the emotions as the size of the vehicles increases.

- It can be noted that for negative emotions (Worry, Stress, Confusion, Fear) the difference is > 0, meaning that the intensity tends to be higher as the size of the vehicle increases.
- For positive emotions (Trust, Safety) difference is <0, meaning that people feel less secure at the increasing of the vehicle size

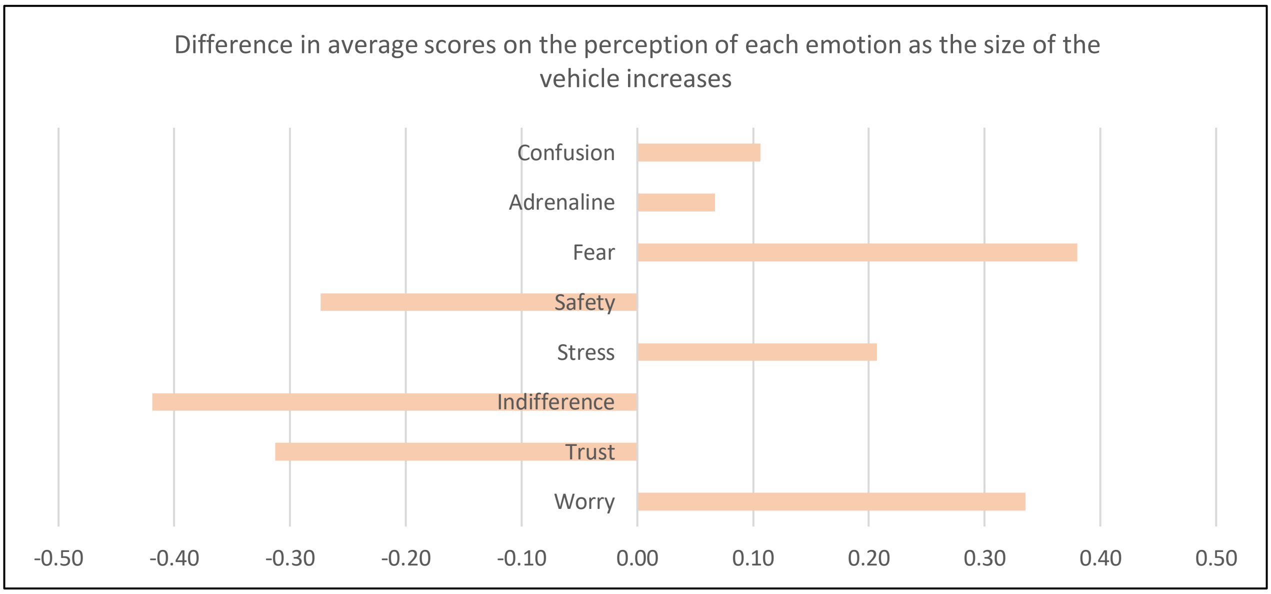


Figure 18

Through the Wilcoxon test it has been analysed the possible influence of vehicle size on emotional responses (*Table 28*). Results indicate correlation with almost all of the emotions under consideration in this research.

Emotions	P-value
Worry	1,61e-05
Stress	0,000803
Fear	1,38e-07
Confusion	0,03423
Safety	1,13e-05
Trust	4,46e-08
Indifference	1,41e-07
Adrenaline	0,07412

Table 28 – P-values of Wilcoxon test on emotional responses

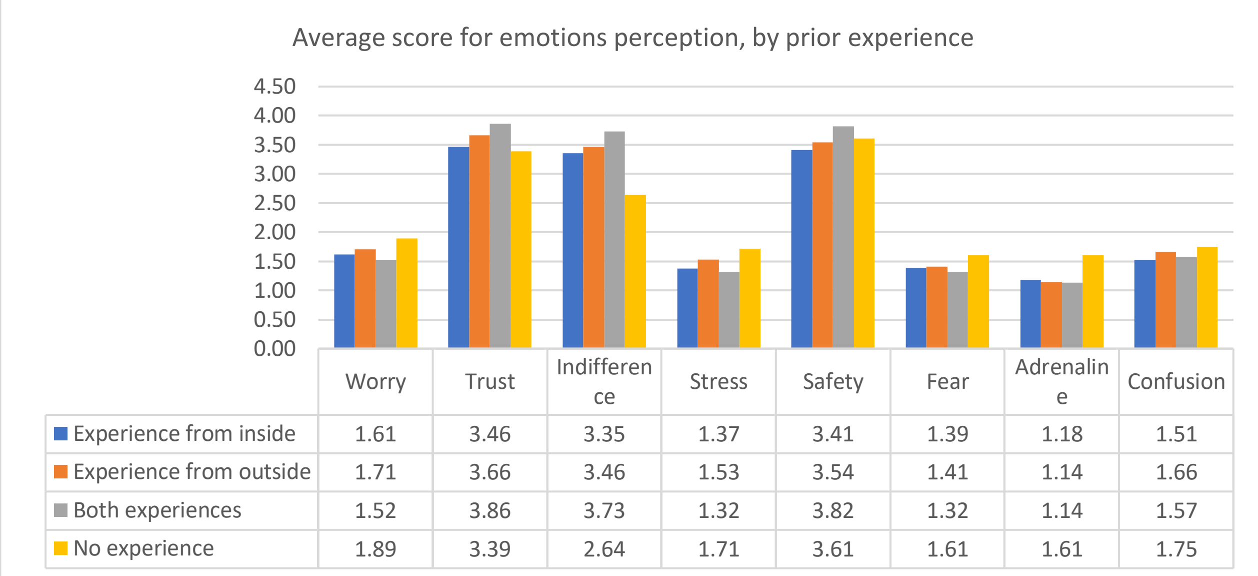
According to the results shown, size influences all emotions except for adrenaline. Looking at the differences in results of the chart, it is safe to assume that as the size of the vehicle increases, people tend to feel less secure and more intimidated.

H8: Prior experience of pedestrians with EV has an effect on their trust. Those with experience on board will show highest scores in positive emotions (Trust and Safety)

Method: Logistic Linear Regression

Outcome: Supported

Figure 19 shows the average score for different emotions, divided by prior experience with EVs. It can be noticed that people with both experiences have a higher score for positive and neutral emotions (Trust, Safety, Indifference) compared to other clusters and lower for negative emotions (Worry, Stress, Fear, Confusion). People with no experience, instead have a lower score for positive and neutral emotions (Trust, Safety, Indifference) compared to other clusters and higher for negative emotions (Worry, Stress, Fear, Confusion). They also have a higher score for Adrenaline.



	Worry	Trust	Indifference	Stress	Safety	Fear	Adrenaline	Confusion
Experience from inside	1.61	3.46	3.35	1.37	3.41	1.39	1.18	1.51
Experience from outside	1.71	3.66	3.46	1.53	3.54	1.41	1.14	1.66
Both experiences	1.52	3.86	3.73	1.32	3.82	1.32	1.14	1.57
No experience	1.89	3.39	2.64	1.71	3.61	1.61	1.61	1.75

Figure 19

Due to the nature of the variables, Logistic Linear Regression is the most suitable method. Tables below show results of the test for *"Trust"* (*Table 29*) and *"Safety"* (*Table 30*). Results indicate that for trust, single experiences are not relevant, while the combination of the two is more significant but only marginally, while for safety, experience from the inside of the EV is almost significant, even if negatively correlated (Value <0), Also, combination of both experiences is strongly correlated with an increase in the perceived emotions.

The impressions from the chart are partially correct: prior experience with EV help pedestrians to feel safer when interacting with them.

TRUST	Value	P-value
Experience from inside	-0,35	0,4
Experience from outside	-0,07	0,89
Both experiences	1,06	0,07

Table 29 – Results of logistic linear regression between prior experience and "Safety"

SAFETY	Value	P-value
Experience from inside	-0,84	0,05
Experience from outside	-0,87	0,07
Both experiences	1,86	1,84e-03

Table 30 - Results of logistic linear regression between prior experience and "Trust"

Additional Analysis

It has been deemed appropriate to test the correlation also between other emotions 8(*from Table 31 to 36*). The same method has been applied. P-values of tables below indicate only adrenaline as emotion influenced by prior experience. Specifically, Experience from inside and from outside seems to be associated with a decrease in perceived adrenaline, meaning that people who already know

EVs are calmer. However, the combination of the two is irrelevant, meaning that one type of experience is enough.

WORRY	Value	P-value
Experience from inside	-0,66	0,11
Experience from outside	0,10	0,84
Both experiences	-0,31	0,61

Table 31 – Results of logistic linear regression between prior experience and "Worry"

INDIFFERENCE	Value	P-value
Experience from inside	0,69	0,08
Experience from outside	0,66	0,14
Both experiences	0,21	0,71

Table 32 – Results of logistic linear regression between prior experience and "Indifference"

STRESS	Value	P-value
Experience from inside	-0,50	0,28
Experience from outside	0,46	0,36
Both experiences	-0,77	0,26

Table 33 – Results of logistic linear regression between prior experience and "Stress"

FEAR	Value	P-value
Experience from inside	-0,61	0,18
Experience from outside	-0,22	0,67
Both experiences	0,19	0,78

Table 34 – Results of logistic linear regression between prior experience and "Fear"

CONFUSION	Value	P-value
Experience from inside	-0,82	0,06
Experience from outside	0,05	0,92
Both experiences	0,31	0,62

Table 35 – Results of logistic linear regression between prior experience and "Confusion"

ADRENALINE	Value	P-value
Experience from inside	-1,16	2,7e-02
Experience from outside	-1,53	3,47e-02
Both experiences	1,33	0,15

Table 36 – Results of logistic linear regression between prior experience and "Adrenaline"

H9: Implementation of signals (visual, acoustic and movement based) is positively correlated with positive emotions (Trust, Safety, Adrenaline) and negatively correlated with negative emotions (Fear, Stress, Worry, Confusion)

Method: Kendall's Tau

Outcome: Supported

The aim of the hypothesis is to understand how emotional responses change at the increase of perceived effectiveness of signal categories. To test the correlation between variables on Likert scale, it has been employed the Kendall's Tau Test to determine on which emotions the perceived effectiveness is significant. According to the results:

- visual signals (*Table 37*) are those which impacts the most emotions. Surprisingly, the tau value is slightly >0 both for positive and negative emotions, indicating a weak positive correlation.

	Worry	Trust	Indifference	Stress	Safety	Fear	Adrenaline	Confusion
Tau	0,15	0,1	0,14	0,13	0,13	0,03	0,02	0,09
P-Value	0,02	0,1	0,02	0,04	0,03	0,7	0,74	0,15

Table 37 – Results of Kendall's Tau test between visual signals' perceived effectiveness and emotional responses

- acoustic signals *(Table 38)* have an effect only on worry of participants. Same as visual signals, the correlation is weak and positive.

	Worry	Trust	Indifference	Stress	Safety	Fear	Adrenaline	Confusion
Tau	0,14	0,09	0,08	0,12	0,06	0,07	0,12	0,12
P-Value	0,02	0,16	0,22	0,07	0,36	0,28	0,07	0,07

Table 38 - Results of Kendall's Tau test between acoustic signals' perceived effectiveness and emotional responses

- movement-based *(Table 39)* signals do not affect negative emotions, while seems to be positively correlated with trust.

	Worry	Trust	Indifference	Stress	Safety	Fear	Adrenaline	Confusion
Tau	-0,02	0,16	0,12	0,07	0,09	0,06	0,08	0,12
P-Value	0,8	0,01	0,06	0,3	0,17	0,35	0,22	0,07

Table 39 - Results of Kendall's Tau test between movement-based signals' perceived effectiveness and emotional responses

By looking at the occurrences matrixes it is possible to have a deeper understanding of the correlation that binds the variables. Following figures are the occurrences matrixes for the emotions that are influences by signals:

- **Visual:** All the significant values in Visual Signals are weakly and positively correlated. That means that as the perceived effectiveness of signals increases, also the intensity of Worry (Figure 20), Stress (Figure 21), Indifference (Figure 22) and Safety (Figure 23) increases. For Worry and Stress there is similar trend, high values of perceived effectiveness of visual signals are concentrated in correspondence of low values of emotion perception, meaning that even if the presence of signal may increase the intensity of these emotions, the intensity remains low enough to be not concerning. For Indifference and Safety there is similar trend, high values of perceived effectiveness of visual signals are concentrated in correspondence of mid/high values of emotion perception, meaning that the presence of signal helps increasing even the intensity of these emotions.

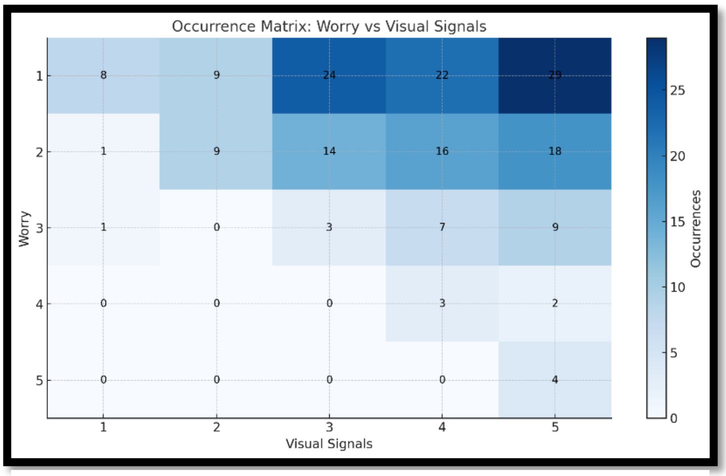


Figure 20

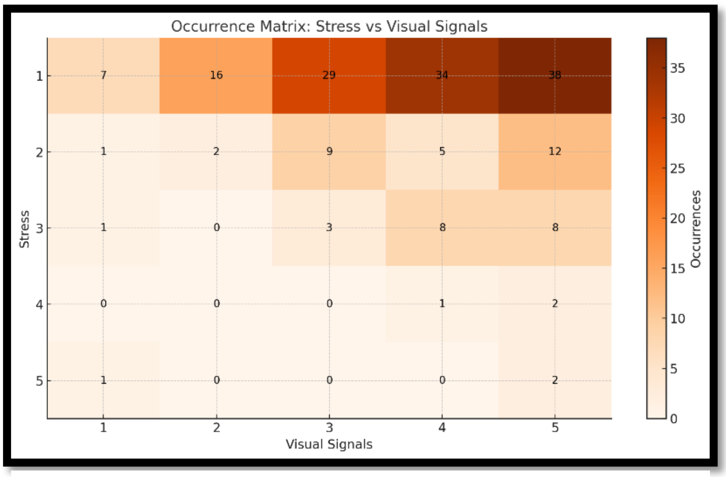


Figure 21

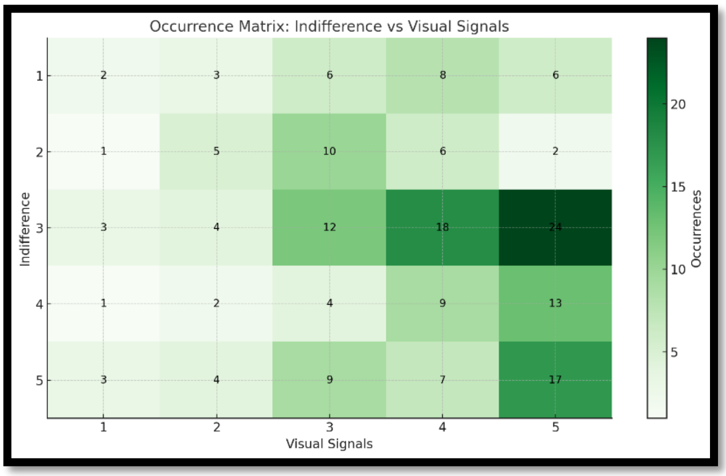


Figure 22

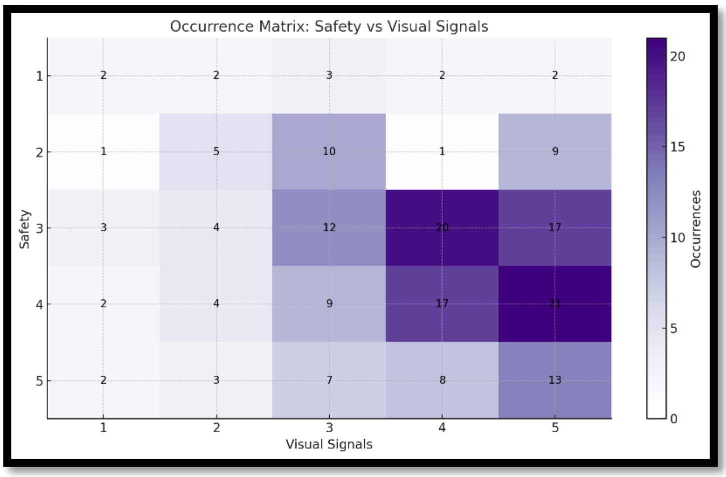


Figure 23

Acoustic: For Acoustic Signals, it appears to be a correlation with the emotion "Worry" (Figure 24). Correlation is positive but weak. As for visual signals, values for intensity of worry are generally low, but since this is the only emotion that seems to be affected, acoustic signals may create a sense of worry in pedestrian without affecting the safety perceived

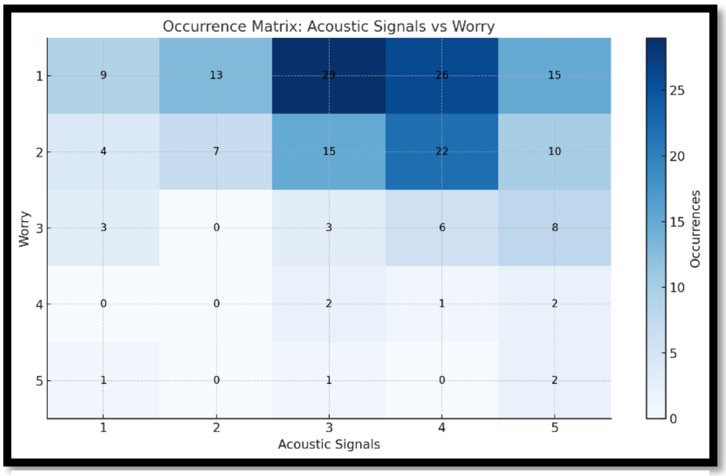


Figure 24

Movement-based: it appears to be a correlation with the emotion "Trust" (Figure 25). Correlation is positive but weak. However, values are focused on the bottom-left corner of the matrix, meaning that even if the correlation is positive, general perceived effectiveness for these signal categories is low. If these signals will be perceived as more effective, they could help to increase Trust in EV, but at the actual state the effect is weak.

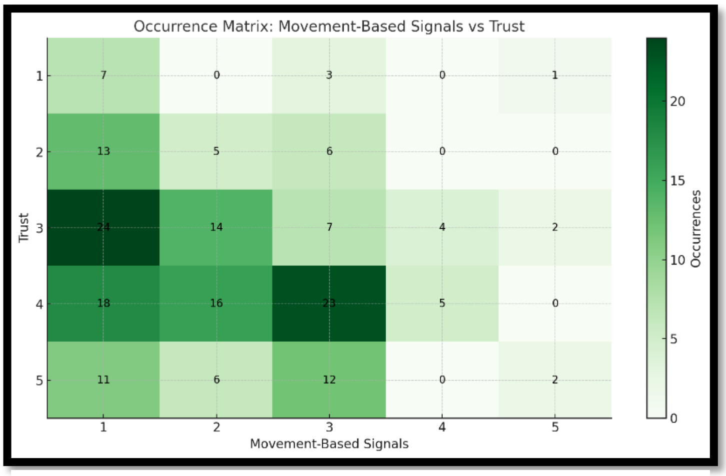


Figure 25

Hypothesis 10: Those who perceive crossing in front of an EV as a threat are more likely to consider the low noise of EV's as a danger.

Method: Chi-squared

Outcome: Supported

The aim of the hypothesis is to verify the reason of the perception of danger associated with EV. Figure 26 shows the number of respondents who consider dangerous crossing in front of an EV, by the perception of low noise. Among people who consider the crossing dangerous, only a minority do not feel as a threat the low noise of EVs. Most of the people who do not consider low noise as a threat also don't perceive the crossing as a danger. However, most of respondents consider the low noise as a threat, indicating a general concern.

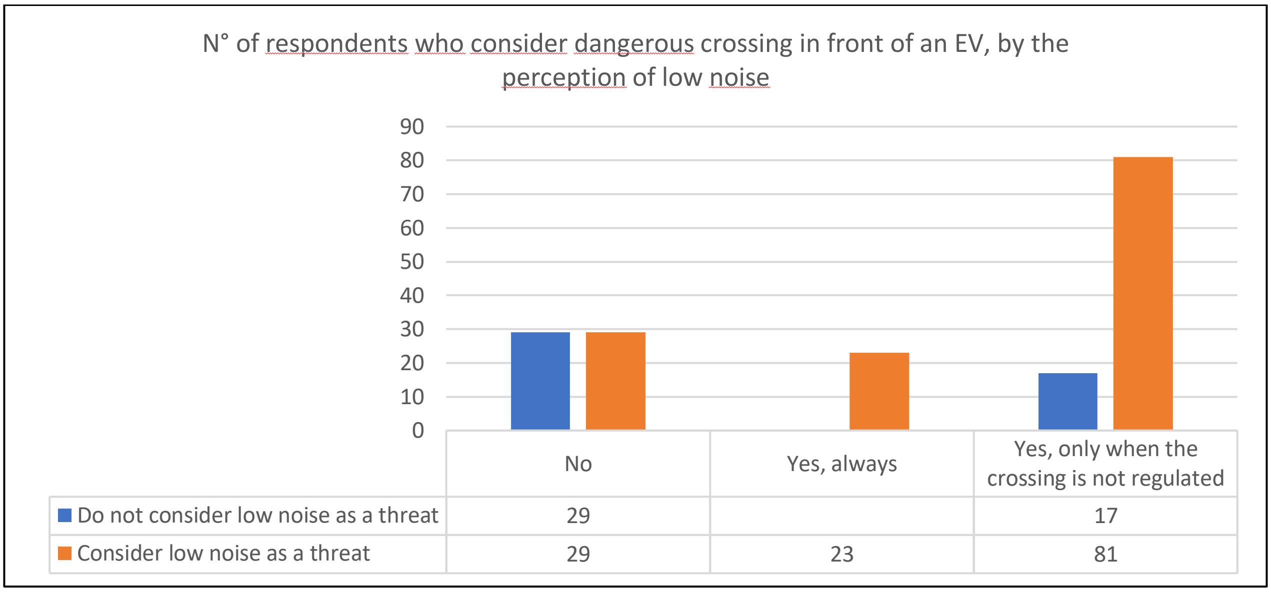


Figure 26

Results suggest the presence of a correlation. To verify it, Table 40 shows the results of a chi-squared test. Numbers clearly indicate the presence of a strong correlation between the two variables (P-value <<0,05).

Chi-squared	P-value
29,47	3,98e-07

Table 40 – Results of the chi-squared test between perception of danger when crossing and perception of low noise

Through the analysis of residual values (*Table 41*), it is possible to understand the type of correlation. For those who do not consider low noise as a threat, are more likely not to consider dangerous the crossing (residuals for «NO» >+2). Consistently, those who consider low noise as a threat are not likely to not consider dangerous the crossing.

Low noise perception	No	Yes, always	Yes, only when the crossing is not regulated
Do not consider as a threat	3,65	-2,43	-1,63
Consider as a threat	-2,14	1,43	0,96

Table 41 – Residuals values of the chi-squared test for perception of low noise

Hypothesis cannot be rejected; noise perception is correlated with the feeling of dangerous during the crossing

H11: People who don't think of crossing in front an EV as a danger, will show lower level of perceived effectiveness all signals' categories (visuals, auditory and movement-based) compared to those who think of it as a safety issue

Method: Kruskal-Wallis

Outcome: Supported

Figure 27 shows the average score perceived effectiveness for signals' families, by perception of danger when crossing in front of an EV. While it seems there is no difference between those who answered "No" and those who answered "Yes, only in absence of regulations", those who consider the crossing always a threat considers visual and acoustic signals as more effective. For the movement-based signals, there is no clear difference between the different responses.

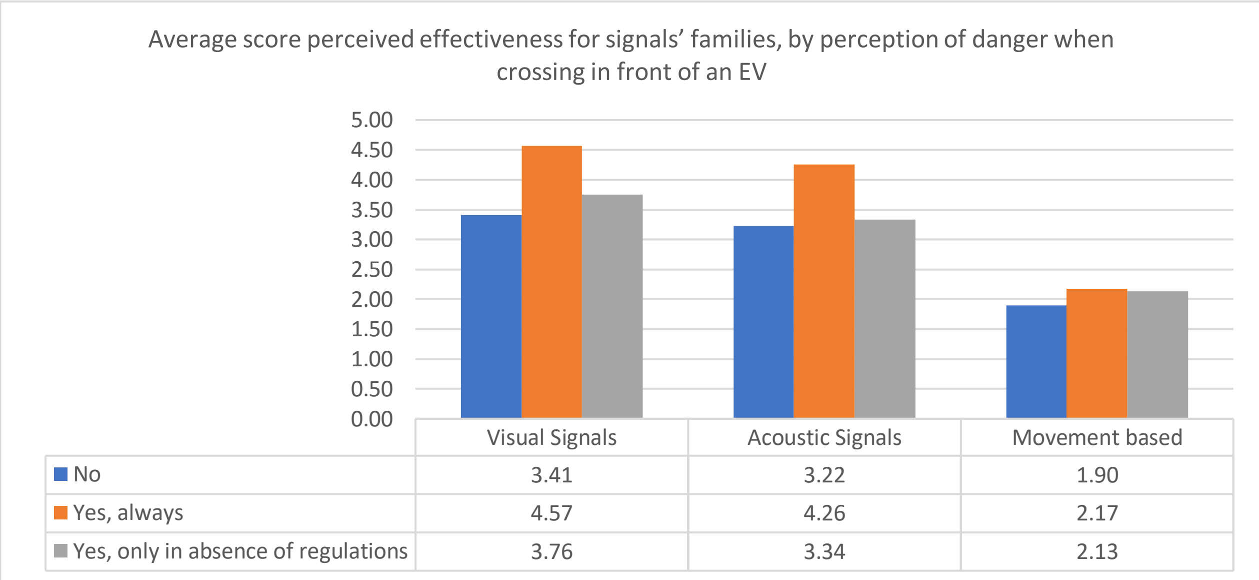


Figure 27

To investigate correlation, it has been employed a Kruskal-Wallis test, the results of which can be seen in Table 42. The numbers confirm the impressions, perception of danger has an influence on the perceived effectiveness of visual and acoustic signals (p-value >0), specifically, those who consider always the crossing as a threat tend to rate these signals as more effective. Movement-based signals instead are not affected.

Categories	**Chi-Squared**	**P-value**
Visual Signals	15,57	4,1e-03
Acoustic Signals	14,9	5,8e-03
Movement based Signals	1,4	0,49

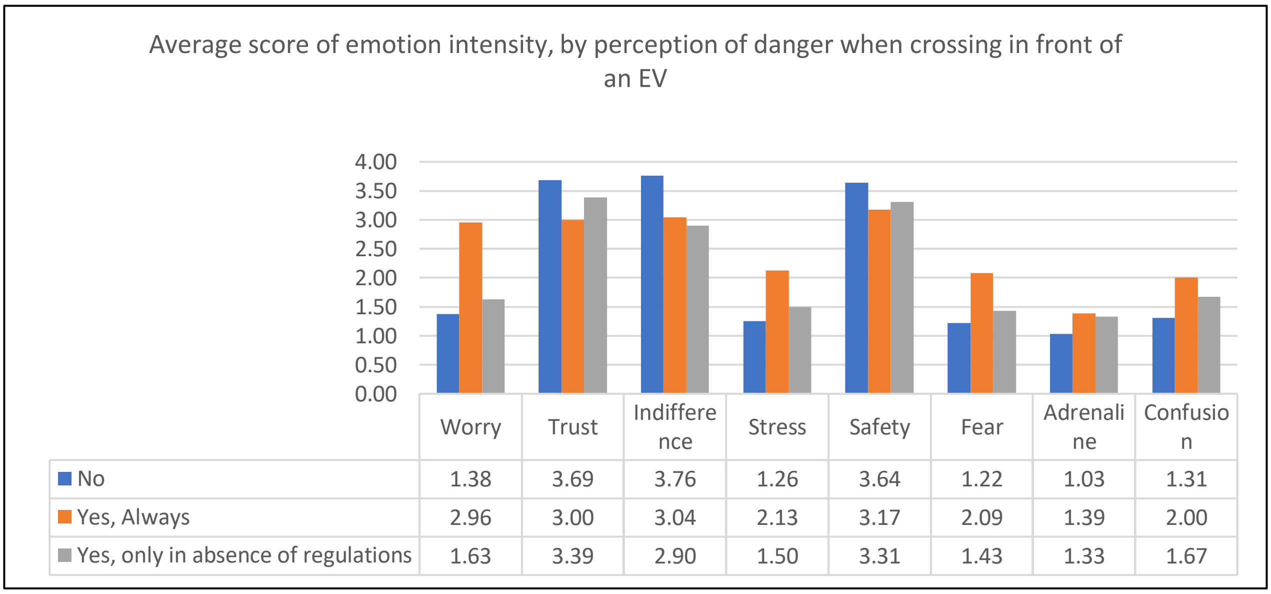
Table 42 – Results of a Kruskal-Wallis test between perception of danger when crossing and signals' effectiveness

Additional analysis

It has been deemed appropriate to investigate the influence of the same independent variable on emotional responses of participants. The same test has been used, considering as dependent variables the emotions in scope of this research.

Figure 28 presents the average score of emotion intensity, by perception of danger when crossing in front of an EV:

- People who don't perceive danger show lower intensity for Worry, Stress, Fear and Confusion, similarly to those who are afraid only in absence of regulations.
- Those who always consider the crossing a danger shows way higher scores in negative emotions compared to other clusters
- Consistently with expectations, participants who answered *"NO"* presents higher values for positive emotions such as trust and safety.
- Adrenaline is the emotion with the least difference between clusters



	Worry	Trust	Indifference	Stress	Safety	Fear	Adrenaline	Confusion
No	1.38	3.69	3.76	1.26	3.64	1.22	1.03	1.31
Yes, Always	2.96	3.00	3.04	2.13	3.17	2.09	1.39	2.00
Yes, only in absence of regulations	1.63	3.39	2.90	1.50	3.31	1.43	1.33	1.67

Figure 28

Through the Kruskal-Wallis test it is possible to determine which emotions are influenced by the perception of danger when crossing. Table 43 below show the results of the test and confirm the preliminary insights: perception of danger when crossing is significant and has an effect on most of negative emotions analysed, but not on the positive emotions.

	Value	P-value
Worry	35,67	1,79e-08
Trust	5,78	0,056
Indifference	15,9	3,4e-04
Stress	10,01	6,6e-03
Safety	3,37	0,18
Fear	12,7	1,7e-03
Adrenaline	9,34	9,4e-03
Confusion	9,99	6,7e-03

Table 43 - Results of a Kruskal-Wallis test between perception of danger when crossing and emotional responses

5.1.3. Discussion of Results

The effectiveness of communication signals used by electric vehicles varies across different modalities, with visual signals consistently ranking as the most effective in terms of clarity and trustworthiness. Acoustic signals and movement-based cues, while beneficial in specific contexts, are often perceived as less intuitive, leading to reduced pedestrian confidence. This aligns with findings from Bazilinskyy et al. (2023), who highlight the importance of synthetic vehicle sounds in enhancing pedestrian safety, especially at lower speeds where EVs are virtually silent. The study also emphasizes that continuous high-frequency tones are more effective in deterring pedestrians from crossing compared to intermittent beeps, which provide less information during inter-pulse intervals. However, these preferences are not universal; they are shaped by demographic characteristics, prior experience, and situational factors.

Demographic in Signal Preferences

Older individuals, particularly those aged 46–60 and 60+, show a clear preference for communication modalities such as colour-coded signals and musical tones. This finding is consistent with research on pedestrian behaviour in relation to eHMIs for automated vehicles, where colour and auditory tones enhance perceived safety (Faas & Baumann, 2021). Furthermore, transportation modes influence signal preferences; motorcyclists show a stronger inclination toward acoustic signals, particularly spoken messages, while public transportation users tend to perceive movement-based signals as less effective. This suggests that personal mobility habits shape expectations regarding vehicular communication.

A demographic divide in the study was observed between urban and rural residents. Urban pedestrians, who encounter EVs more frequently, reported higher levels of trust in EV communication signals and found spoken and movement-based cues more intuitive. This aligns the literature, which finds that urban populations are more exposed to EV infrastructure, such as charging stations and smart traffic systems, leading to greater acceptance of EVs (Rahman & Thill, 2023). Koh and Yuen (2023) also emphasize that urban areas experience higher traffic congestion, air pollution, and technological integration, making EV adoption more desirable and increasing pedestrian confidence in EV safety and benefits.

In contrast, rural pedestrians in the study expressed greater hesitancy toward spoken messages as a form of communication and preferred high-visibility signals such as LED panels or colour-coded indicators. This aligns with Zhao et al. (2024), who found that rural residents generally display more scepticism toward EVs due to lower exposure to the technology and infrastructural limitations. Furthermore, limited access to EV-friendly infrastructure, such as charging stations and well-maintained roads, contributes to the perceived impracticality of EV adoption in rural areas (Koh & Yuen, 2023). These findings reinforce the necessity of customizable eHMI solutions that cater to different environmental and demographic contexts. For urban settings, integrating auditory and movement-based signals may be effective, whereas in rural areas, visual signals with stronger emphasis on colour contrast and large displays could be more appropriate.

Influence of Experience on Trust and Safety Perceptions

Prior experience with EVs significantly influences pedestrians' trust and safety perceptions during interactions. Studies indicate that hands-on experience with EVs leads to increased comfort and confidence in navigating interactions with these vehicles (Rezvani et al., 2015). Both in-vehicle and external experiences contribute to improved safety perceptions, reinforcing the need for public exposure to EVs through education and urban planning initiatives. Additionally, Zhao et al. (2024) found that pedestrians tend to develop their trust in vehicles through direct and indirect experiences, emphasizing the role of repeated exposure in shaping behaviour. The results also highlight that individuals with exposure to EV simulations exhibit greater confidence in engaging with EVs compared to those with only on-road experience. This suggests that structured, controlled exposure to EV interactions (such as public demonstrations or virtual reality simulations) could be effective in reducing uncertainty and improving public trust in EV communication signals.

The Role of Noise in Perceived Danger

The quiet nature of EVs affects pedestrians' subjective perception of risk, underscoring the need for auditory cues in urban traffic. Faas & Baumann (2021) found that pedestrians feel notably less secure in the absence of traditional engine sounds, a concern that has led to regulatory mandates requiring EVs to emit artificial sounds at low speeds. Similarly, Bazilinskyy et al. (2023) demonstrated that continuous high-frequency sounds are more effective in deterring pedestrians from crossing than intermittent beeps. This evidence supports the argument that auditory signals should be carefully designed to balance safety and annoyance. Notably, research suggests that sound pitch, modulation, and frequency should be tailored to urban versus suburban contexts, as different environmental conditions affect auditory perception. Pedestrian safety research has also highlighted that missing auditory cues in EVs pose a risk particularly in scenarios with limited visibility or high background noise, making auditory enhancements crucial for pedestrian interaction. The effectiveness of communication signals is highly situational. Still Faas & Baumann (2021) confirms that traffic density and vehicle speed play crucial roles in determining the success of eHMI interventions. Interestingly, contrary to expectations, residential neighbourhoods do not significantly impact perceptions of communication effectiveness. This could be due to an urban-skewed sample in the study, as prior literature suggests that quieter environments generally heighten the reliance on auditory cues.

Vehicle Size as a Psychological Factor

Increasing vehicle size elicits stronger emotional reactions, including fear and concern, which underscores the need for tailored eHMI designs that consider vehicle size as a psychological determinant in pedestrian-vehicle interactions. The study’s findings align with existing literature indicating that pedestrians exhibit greater hesitation when encountering larger AVs or EVs due to the increased perceived risk of injury (Faas & Baumann, 2021).

Practical Implications of the Findings

The findings of this study have several important practical implications for EV design, urban planning, and regulatory policies:

The varying preferences for communication signals across demographics and transportation modes indicate the need for customizable eHMI designs. For instance, urban environments may benefit from a combination of visual and acoustic signals, while rural areas might require enhancements in non-verbal visual indicators such as LED panels or colour-coded light signals. Research suggests that multimodal eHMI solutions combining light and sound may be particularly effective in reducing ambiguity in pedestrian-vehicle interactions (Dey et al., 2024).

Policymakers should consider adapting current regulations on EV auditory signals to better reflect pedestrian preferences. Instead of a one-size-fits-all approach, allowing manufacturers to fine-tune sound characteristics, such as frequency or tone, based on environmental factors and pedestrian feedback, may enhance safety without increasing noise pollution. Current legislation mandates synthetic sounds for EVs at low speeds, but researchers emphasize the importance of optimizing sound characteristics for better pedestrian engagement (Bazilinskyy et al., 2023).

Given the positive correlation between experience and trust in EVs, public awareness campaigns and interactive demonstrations can significantly improve safety outcomes. Municipalities could introduce VR-based EV crossing simulations in traffic education programs to familiarize pedestrians with EV behaviour. Research indicates that pedestrian familiarity with eHMI systems, whether through direct or observational experience, plays a crucial role in trust development (Zhao et al., 2024).

As larger vehicles cause greater pedestrian hesitation, city planners and automakers should ensure that larger EVs (e.g., electric buses or delivery trucks) incorporate more pronounced visual signals and slower approach speeds in high-footfall areas. Deploying augmented reality projections or road surface indicators in smart crosswalks could further mitigate pedestrian apprehension (Tabone et al., 2023).

5.2. Autonomous Vehicles

The methodology will follow the same approach used for the EV section. The analysis will start by showing the distribution of the demographic variables. The key variables include:

- Age (In years)
- Gender
- Study Degree
- Neighbourhood of residence
- Ownership of a driver's license
- Most frequent means of transportation used

However, the AV survey was delivered without strict geographical constraints, therefore is not possible to do a comparison with the population.

5.2.1. Sample Description

This section aims to provide a descriptive overview of the sample involved for the AVs research.

For the AV survey 183 responses have been gathered. An operation of data cleaning has been done, resulting in 4 responses deleted, meaning that analysis has been done using 179 responses. Contrary to the survey for EV, the sample pool was international, not restricted to Italy. Participants are very widespread from all over the globe, making impossible to do a cluster based on nationality.

Figures 29-30-31-32-33-34 show graphically the distribution of each of the key demographic variables.

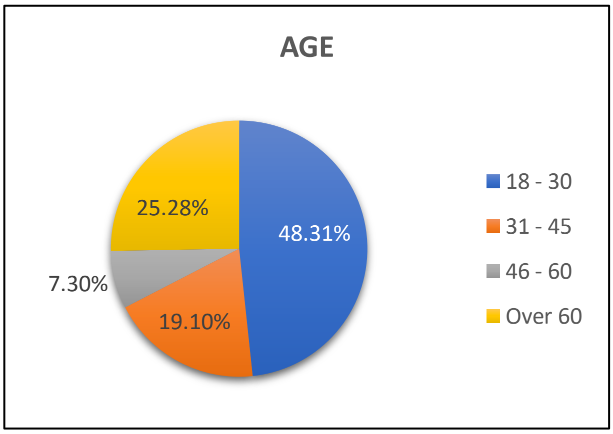


Figure 29

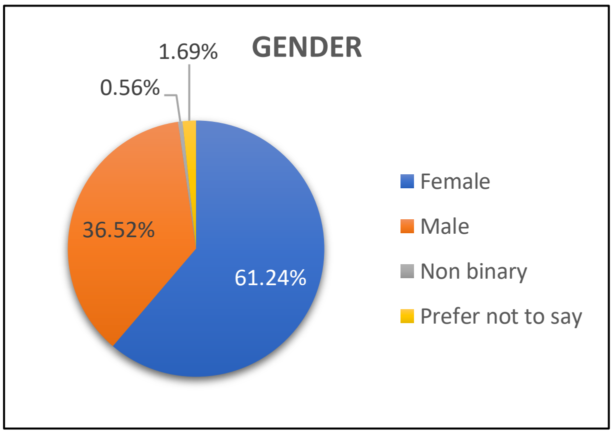


Figure 30

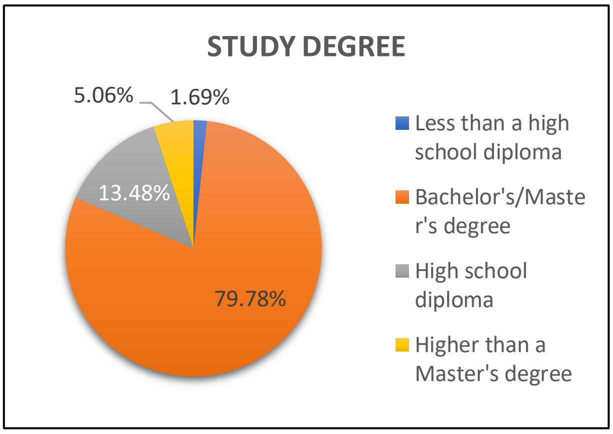


Figure 31

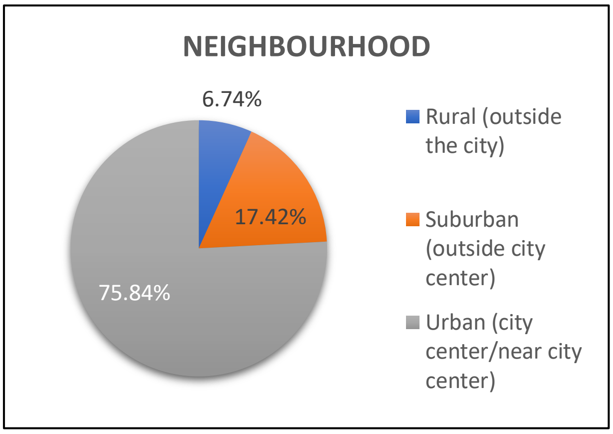


Figure 32

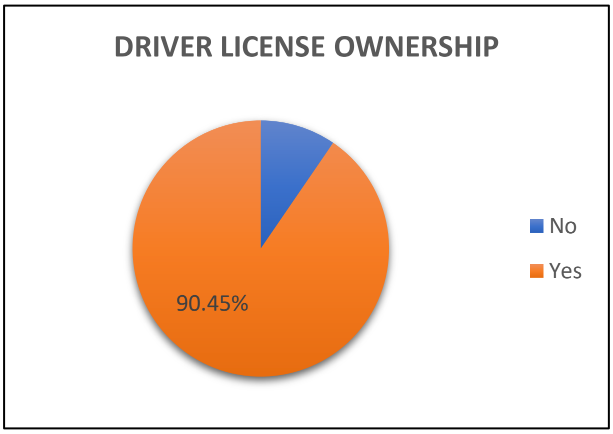


Figure 33

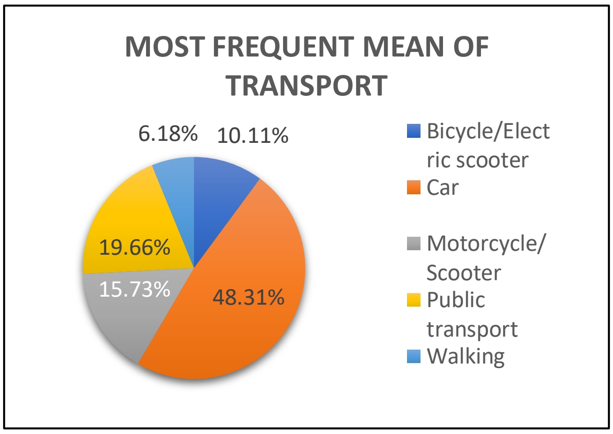


Figure 34

5.2.2. Findings

Each of the hypothesis will be tested according to the methodology described before. This section aims to delve into a punctual analysis of the hypothesis in order to gather the findings and draw conclusions about the perception and emotional responses of pedestrians when interacting with AVs

H1: People who don't think of crossing in front an AV as a danger, will show lower level of perceived effectiveness all signals' categories (visuals, auditory and movement-based) compared to those who think of it as a safety issue

Method: Kruskal-Wallis

Outcome: Not Supported

Figure 35 shows the average score perceived effectiveness for signals' families, by perception of danger when crossing in front of an AV, both graphically and quantitively. It can be noted that visual signals are those with highest perceived effectiveness independently from the cluster, while the difference between acoustic and movement based is less significative. However, from the chart looks like there is no other significant difference between the three clusters in terms of perceived effectiveness.

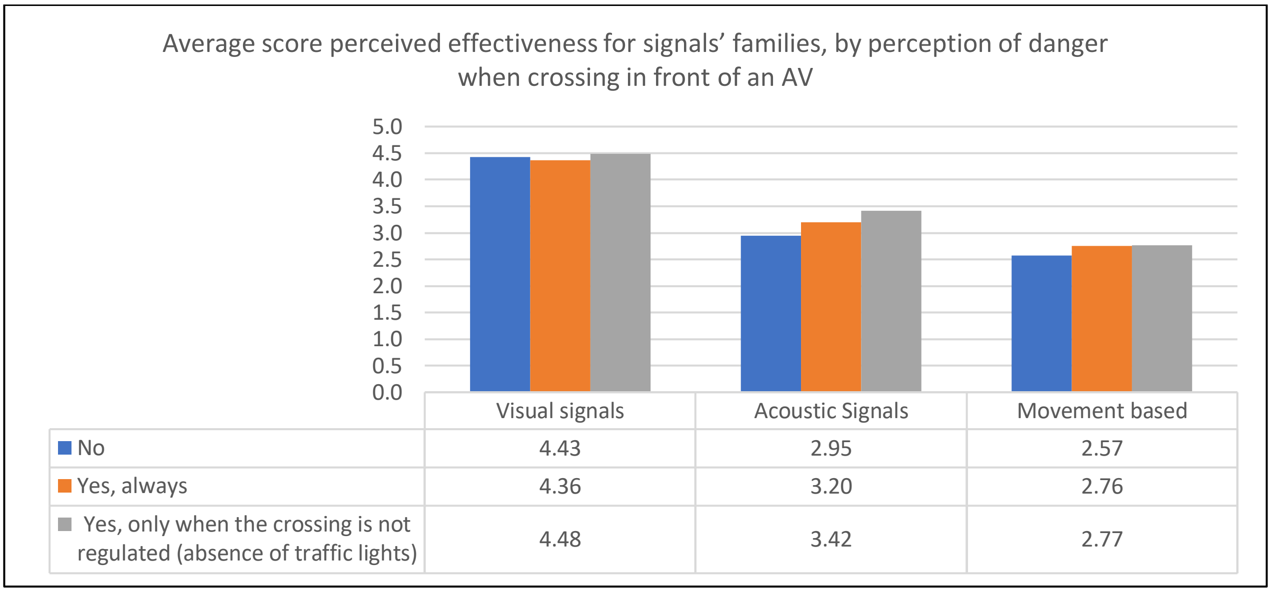


Figure 35

To test the correlation between variables, the most appropriate test is the non-parametric Kruskal-Wallis. Table 44 shows the results of the test:

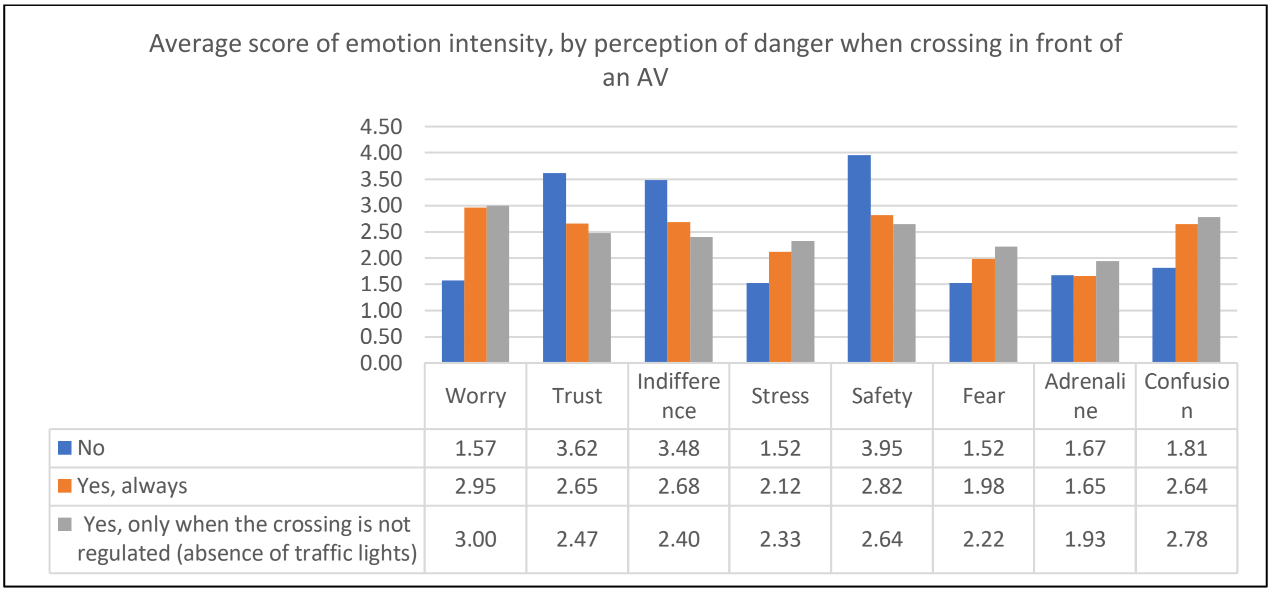
Signal Category	Chi-squared	P-value
Visual	0,67	0,71
Acoustic	3,67	0,13
Movement Based	0,73	0,69

Table 44 – Results of Kruskal-Wallis test between signal categories and perception of danger when crossing in front of an AV

All p-values observed are >0,05, meaning that the test does not have statistic relevance, therefore there is no proof of correlation between the perceived effectiveness of signals and the perception of danger when crossing in front of an AV.

Additional analysis

However, during the analysis it has been deemed appropriate to test the emotional response of pedestrians as well. Figure 36 shows the average score of emotion intensity, by perception of danger when crossing in front of an AV:



	Worry	Trust	Indifference	Stress	Safety	Fear	Adrenaline	Confusion
No	1.57	3.62	3.48	1.52	3.95	1.52	1.67	1.81
Yes, always	2.95	2.65	2.68	2.12	2.82	1.98	1.65	2.64
Yes, only when the crossing is not regulated (absence of traffic lights)	3.00	2.47	2.40	2.33	2.64	2.22	1.93	2.78

Figure 36

From the chart we can see significant differences:

- People who don't perceive danger show lower intensity for Worry, Stress, Fear and Confusion
- Opposite trend is for Trust, Safety and indifference
- Adrenaline is the emotion with the least difference between clusters

To test the statistic correlation, the most suitable test is the non-parametric Kruskal-Wallis. Table 45 shows the results:

Signal Category	**Chi-squared**	**P-value**
Worry	29,75	3.46e-07
Trust	18,22	1,11e-03
Indifference	11,84	2,6e-02
Stress	11,9	2,6e-02
Safety	22,63	1,22e-05
Fear	10,49	5,2e-02
Adrenaline	3,29	0,19
Confusion	12,1	2,3e-02

Table 45 – Results of Kruskal-Wallis test between emotional responses and perception of danger when crossing in front of an AV

The values of *"Chi-squared"* are quite high, indicating significant differences between groups. Looking at the p-values obtained, most are <0,05, meaning that perception of danger when crossing is significant and influences all emotions analysed, except for adrenaline and fear (even if for the latter is almost significant).

This insight is relevant even if out of the perimeter of the hypothesis.

H2: Favourite mean of transportation affects preferences for the signals categories (visuals, auditory and movement-based)

Method: Kruskal-Wallis

Outcome: Supported

Figure 37 shows the average score for the different signals' families, divided by the most frequent means of transport.

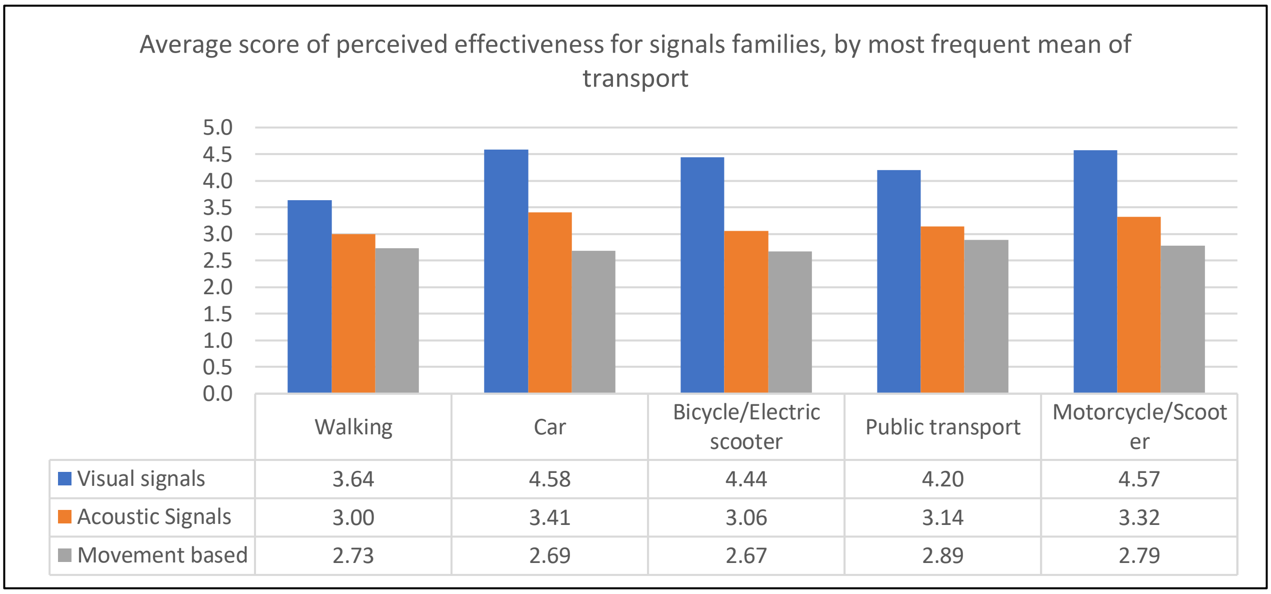


Figure 37

It can be noticed that:

- Visual signals are perceived as highly effective in general
- People who usually walk show lower average scores for visual signals compared to other clusters.

To test the correlation between variables, the most appropriate test is the non-parametric Kruskal-Wallis. Table 46 the results of the test:

Signal Category	**Chi-squared**	**P-value**
Visual	18,07	0,12e-02
Acoustic	3,33	0,5
Movement Based	0,73	0,95

Table 46 – Results of Kruskal-Wallis test between signal categories and transport habits

According to the results, the signal category influenced by the most frequent mean of transport is the visual, as already detected from the chart. However, this test does not explain the type of correlation. To achieve this, is necessary to run a post-hoc test. The most suited choice is the Dunn's test, which gives information regarding the type of correlation between groups. Table 47 shows results for the categories that has proven to be significant.

Comparison	Z	P unadj.	P adj
Car - Walking	3,64	0,27e-03	0,27e-03
Motorcycle/Scooter - Walking	3,27	0,11e-02	0,11e-02

Table 47 – Dunn's test results between transport habits for visual signals

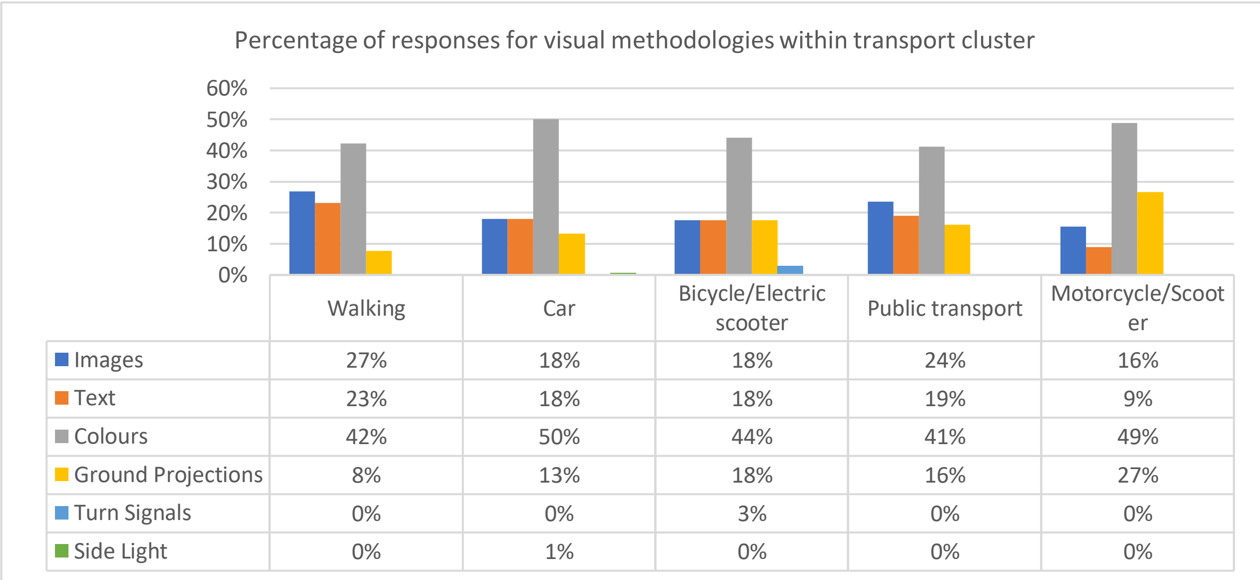
There is a significative difference in the choices between the two clusters. High values of *"Z"* suggest that people who walk tend to show lower level of perceived effectiveness compared to the other clusters ("Car" and "Motorcycle/Scooter"), as detected previously from the chart.

Additional analysis

The next step involves an investigation regarding the influence that the most frequent means of transport may have on the preference of signals methodology. The following histograms show the percentages of responses for Visual, acoustic and movement-based signals, within transport cluster.

VISUAL

For visual signals *"Colours"* is by far the favourite methodology by respondents, independently from the cluster (*Figure 38*)



	Walking	Car	Bicycle/Electric scooter	Public transport	Motorcycle/Scooter
Images	27%	18%	18%	24%	16%
Text	23%	18%	18%	19%	9%
Colours	42%	50%	44%	41%	49%
Ground Projections	8%	13%	18%	16%	27%
Turn Signals	0%	0%	3%	0%	0%
Side Light	0%	1%	0%	0%	0%

Figure 38

The chart does not show any significant differences in trends between clusters. To investigate the statistic correlation between the variables, Chi-squared is the most suitable when dealing with binary variables. Table 48 shows the results of the test

Visual	Images	Text	Colours	Projections on the ground	Turn signals	Side light

Chi-squared Value	7,86	7,21	2,92	5,53	8,94	1,08
P-value	0,09	0,13	0,57	0,24	0,16	0,9

Table 48 – Results of Chi-squared test between visual signal signals and transport habits

The results confirm the first impression, means of transport does not influence the choice of favourite visual methodology, there is no significant difference between groups.

ACOUSTIC

For acoustic signals, *"Warning Sounds"* is the favourite methodology among clusters, which show a very similar trend for other signals as well. The only cluster that differs significantly from others is *"Walking",* which shows a preference for *"Spoken Messages" (Figure 39)*

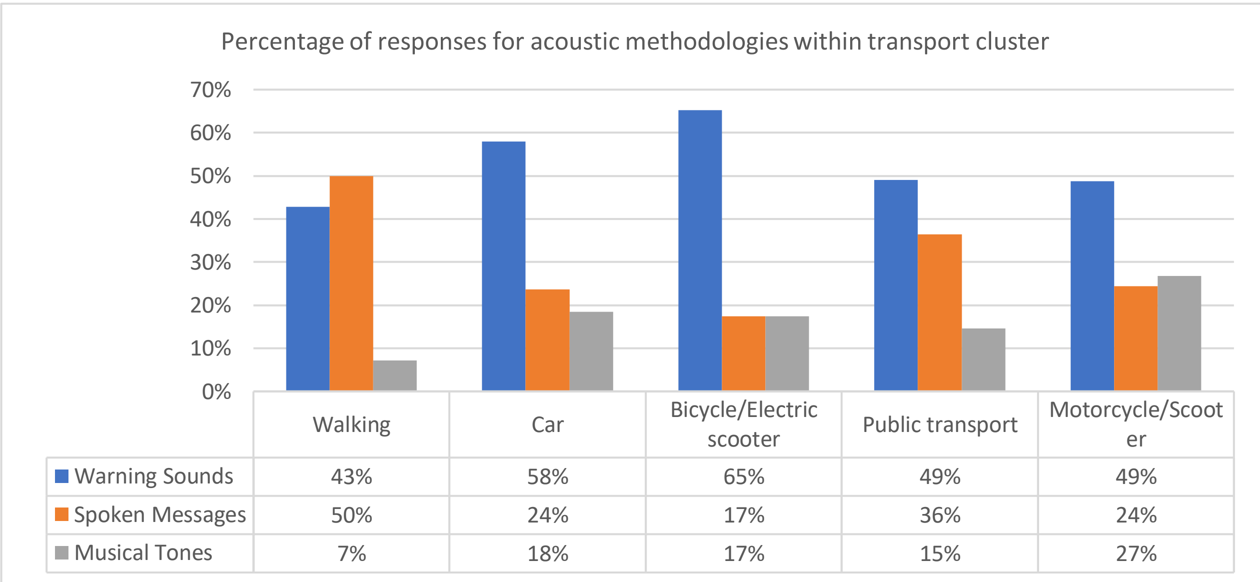


Figure 39

From the chart a possible correlation between the cluster *"Walking"* and the acoustic signals can be noticed. This is confirmed by the results of the Chi-squared test *(Table 49)*.

Acoustic	Warning Sound	Musical Tones	Spoken Messages
Chi-squared Value	7,05	4,67	12,41
P-value	0,13	0,32	0,02

Table 49 - Results of Chi-squared test between acoustic signal signals and transport habits

The p-value for the methodology *"Spoken Messages"* is <0,05. The analysis of residual values explains further the correlation between the variables (*Table 50)*.

- The *"Public Transport"* cluster shows a high residual for the response "Yes" (1.81), suggesting that participants in this group respond "Yes" more frequently than expected. This residual is close to the threshold for significance.
- Participants who walk have a positive residual for the response "Yes" (1.365), indicating a slight tendency toward a higher number of "Yes" responses.

Spoken Messages	No	Yes
Walking	-1,07	1,36
Car	0,8	-1,02
Bicycle/electric scooter	0,86	-1,1
Public transports	-1,43	1,81
Motorcycle/scooter	0,17	-0,21

Table 50 – Residual values of the Chi-squared test between "Spoken messages" and transport habits

MOVEMENT-BASED

For movement-based signals, "Rearview Mirrors" emerges as the preferred approach across all clusters, which exhibit a consistent trend in their preferences for other signals. The only notable variation is observed with *"Public Transport",* although these differences do not appear to be statistically significant *(Figure 40)*.

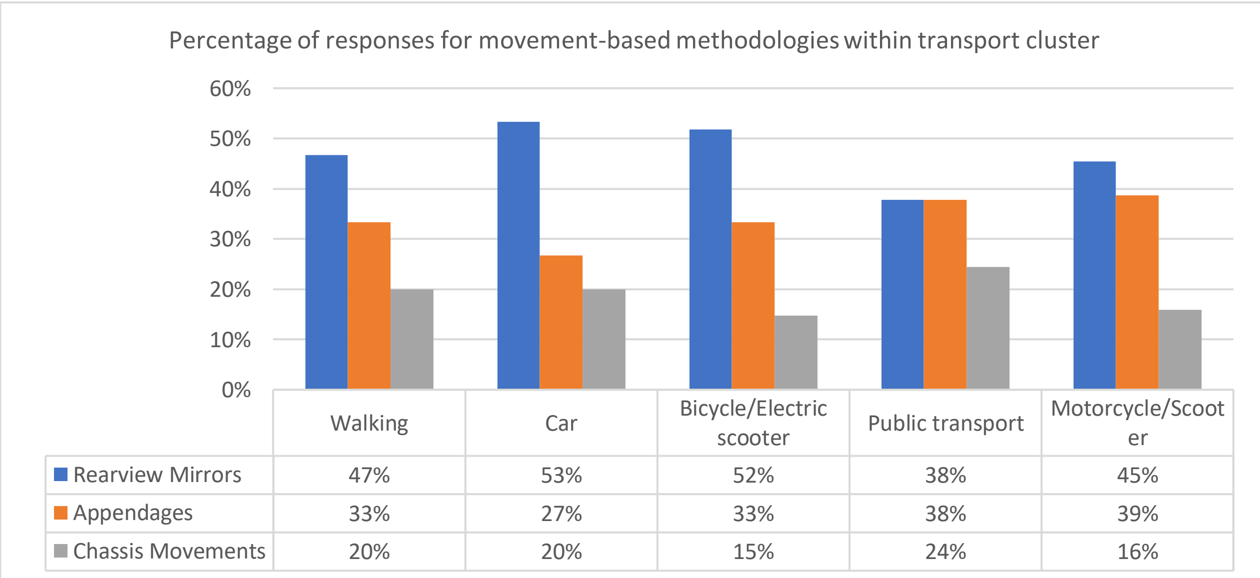


Figure 40

After the Chi-squared test, the first impression is confirmed: among Movement based signals, means of transport seems to have no correlation with any methodology *(Table 51)*.

Movement based	Rearview Movement	Chassis Movement	Appendages Movement
Chi-squared Value	8,79	0,62	5,27
P-value	6,6e-02	0,97	0,26

Table 51 - Results of Chi-squared test between movement-based signal signals and transport habits

H3: Pedestrians who possess a driver's license will report higher levels of understanding (less Confusion) and trust in AV compared to those without a driver's license.

Method: Kruskal-Wallis

Outcome: Not Supported

The goal of the hypothesis is to understand if the knowledge of road rules and behaviour may influence the emotional responses of participants. Figure 41 shows the average score of emotion intensity, divided by ownership of driver license. From the chart it is noticed:

- Ownership of driver license seems to have a small positive effect on positive emotions, since owners show higher scores for trust and safety
- It also has positive effect on negative emotions, reducing their intensity (*Worry, Fear, Stress*)
- The only exception is Confusion: results between the two clusters are similar, however those who do not own a driver license show slightly less confusion perceived

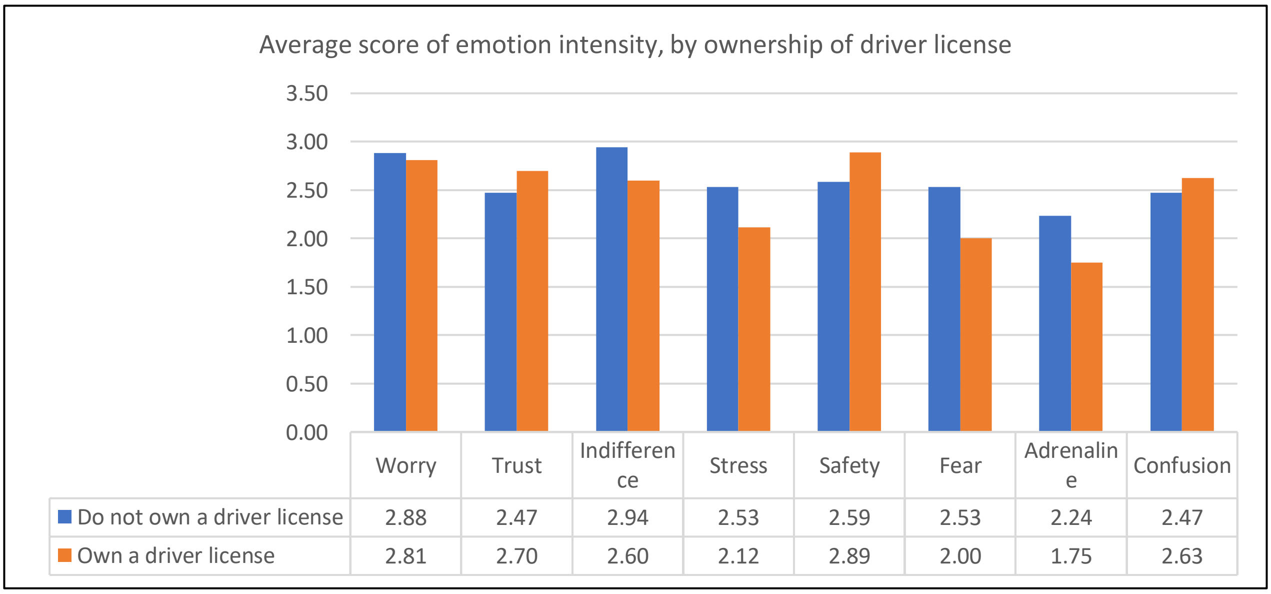


Figure 41

To check on statistical significance, a Kruskal-Wallis test has been performed between the gender and the emotions. According to results in Table 52, ownership of a driver license is significant solely on fear perception, meaning that the hypothesis is partially correct: ownership does not influence the understanding, but it has an effect on fear, which is less intense for those who have a driver license.

	Value	P-value
Worry	0,06	0,81
Trust	0,46	0,5
Indifference	1,72	0,19
Stress	2,39	0,12
Safety	0,7	0,4
Fear	4,34	3,7e-02
Adrenaline	2,66	0,1
Confusion	0,25	0,62

Table 52 – Results of Kruskal-Wallis between emotional responses and driver license ownership

H4: Different age clusters will show different preferences for the signals categories (visuals, auditory and movement-based)

Method: Kruskal-Wallis

Outcome: Not Supported

The figure below shows the average score for the different signals' families, divided by age cluster:

- Visual signals are those perceived with highest effectiveness for every age cluster, way higher than acoustics (more accentuated than EVs).
- Movement based signals are those with the lowest perceived effectiveness for each age cluster
- From the chart there is no particular difference in trends among clusters than can be noticed

From Figure 42 we can assume the absence of correlation between the variables.

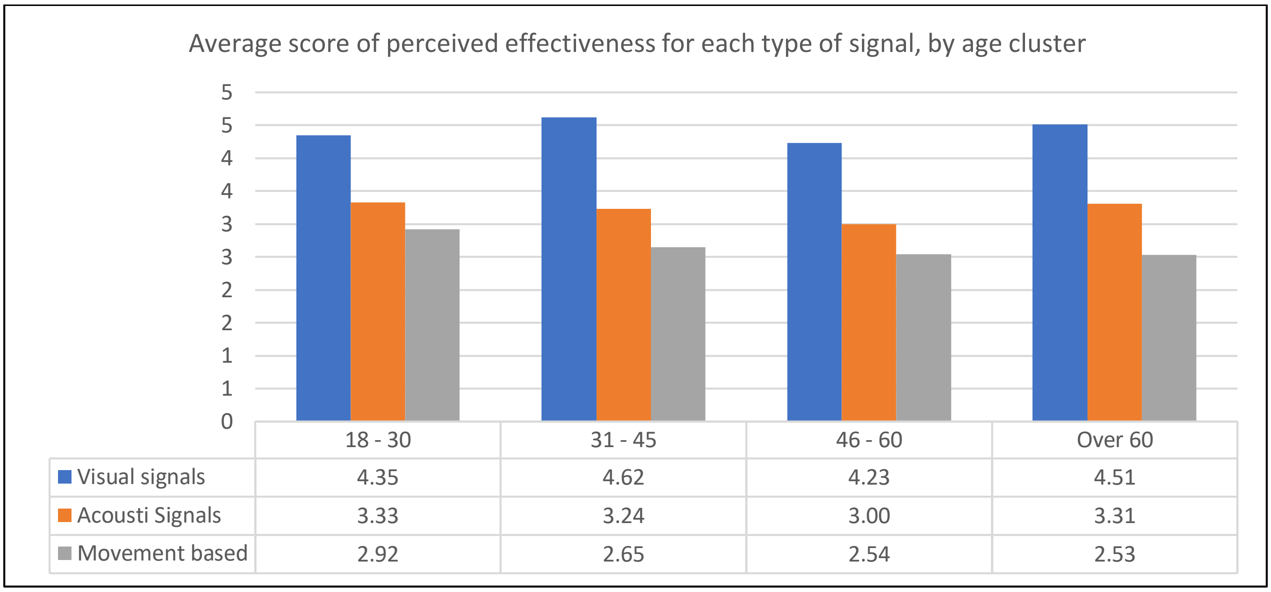


Figure 62

To check on statistic correlation, a Kruskal-Wallis test has been performed on signals for each age group. Results in Table 53 indicate that the preliminary impression is correct: age does not influence the perceived effectiveness of signals categories (all p-values >0).

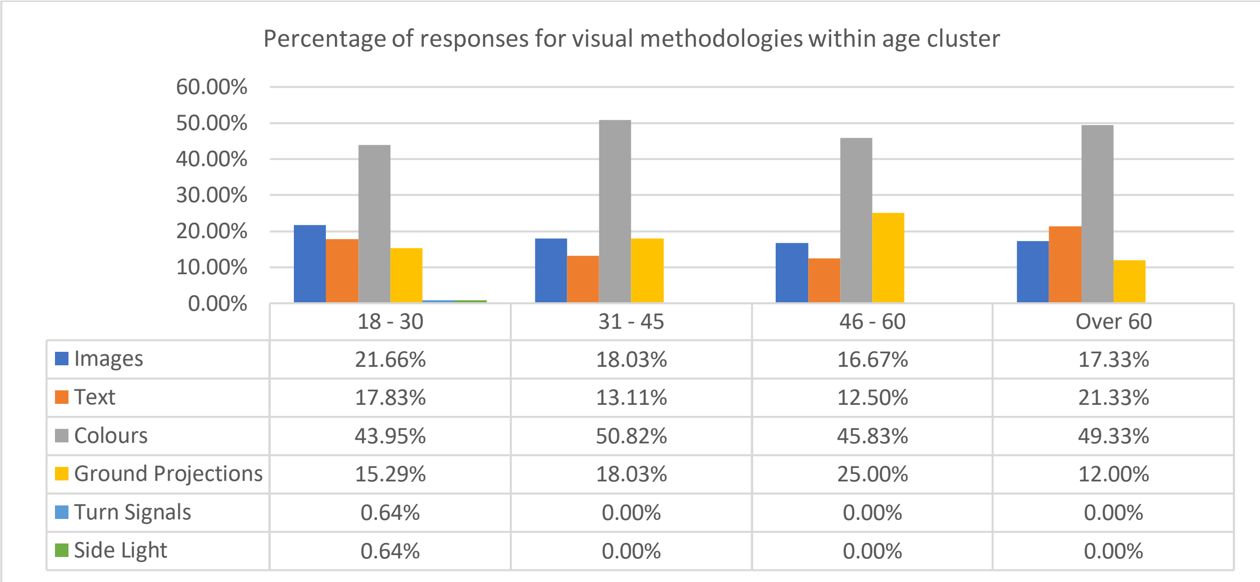
Categories	**Chi-Squared**	**P-value**
Visual Signals	4,75	0,19
Acoustic Signals	0,88	0,83
Movement based	5,02	0,17

Table 53 – Results of Kruskal-Wallis test between signal categories and age clusters.

Additional analysis

The goal is to investigate the possible preferences of age groups on the choice of each signal methodology. The chart below shows the percentage of responses for visual signals within age cluster.

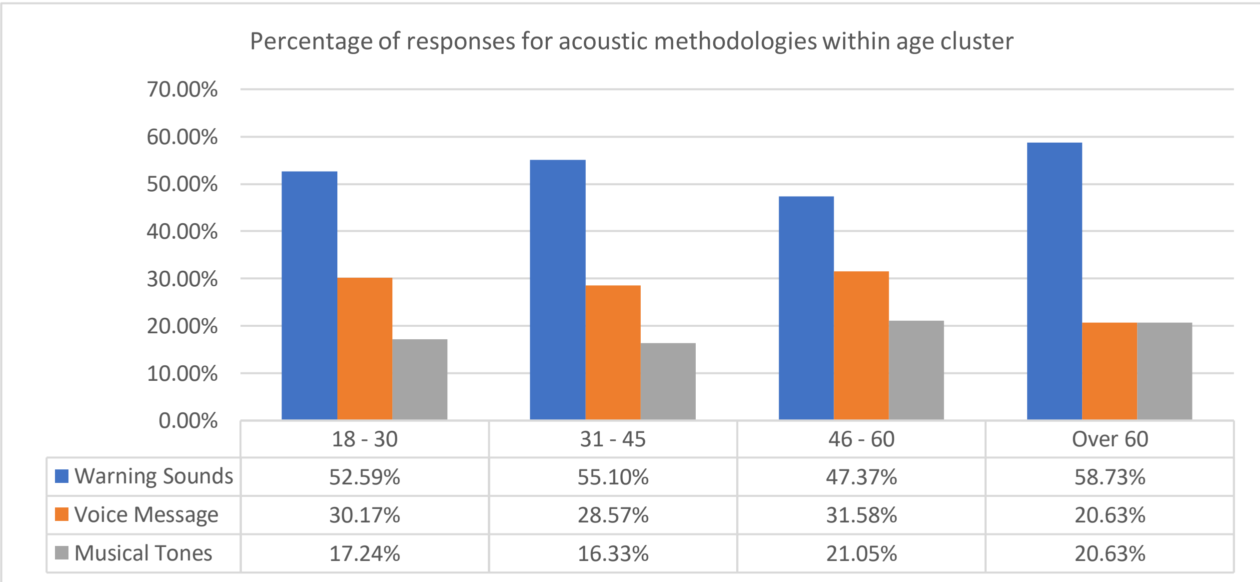
Visual signals: Colours are by far the most preferred choice for all clusters. Participants over 60 years of age are those who present some minimum differences, showing slightly higher preference for the methodology "*Text*" and lower preference for "*Ground Projections*". The methodology "*Turn Signals*" and "*Side Light*" are negligible *(Figure 43)*.



	18 - 30	31 - 45	46 - 60	Over 60
Images	21.66%	18.03%	16.67%	17.33%
Text	17.83%	13.11%	12.50%	21.33%
Colours	43.95%	50.82%	45.83%	49.33%
Ground Projections	15.29%	18.03%	25.00%	12.00%
Turn Signals	0.64%	0.00%	0.00%	0.00%
Side Light	0.64%	0.00%	0.00%	0.00%

Figure 43

Acoustic Signals: Warning sounds are the most preferred methodology among clusters. Participants over 60 present the same degree of preference for voice messages and musical tones *(Figure 44)*.



	18 - 30	31 - 45	46 - 60	Over 60
Warning Sounds	52.59%	55.10%	47.37%	58.73%
Voice Message	30.17%	28.57%	31.58%	20.63%
Musical Tones	17.24%	16.33%	21.05%	20.63%

Figure 44

Movement-based signals: Participants prefer movement of rearview mirrors, independently from the age cluster. This is even more enhanced among over 60 *(Figure 45).*

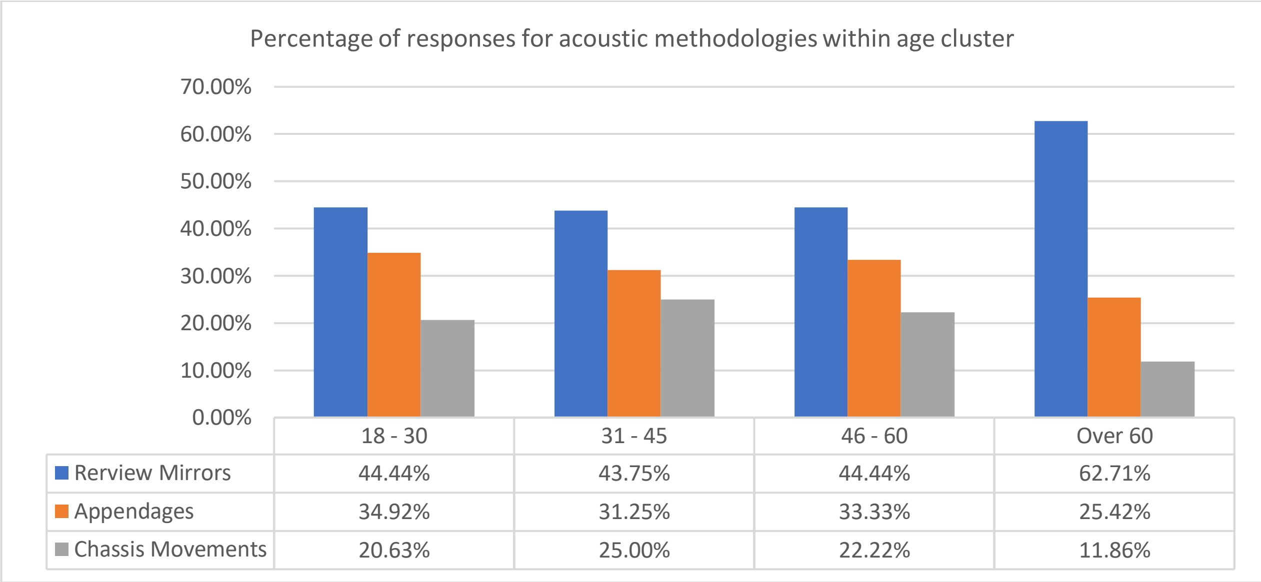


Figure 45

The correlation it has been investigated through a Chi-squared test. However, results of Tables 54-55-56 indicate that age groups do not have any influence on the choice of signal signals (all p-values are <0).

VISUAL	**Images**	**Text**	**Colours**	**Projections on the ground**	**Turn signals**	**Side light**
Chi-squared Value	1,72	1,81	2,13	3,87	1,08	1,08
P-value	0,63	0,61	0,54	0,27	0,78	0,78

Table 54 – Results of Chi-squared test between visual signal signals and age clusters

ACOUSTIC	**Warning Sound**	**Musical Tones**	**Spoken Messages**
Chi-squared Value	2,61	2,36	0,76
P-value	0,47	0,5	0,86

Table 55 - Results of Chi-squared test between acoustic signal signals and age clusters

MOVEMENT BASED	**Rearview Movement**	**Chassis Movement**	**Appendages Movement**
Chi-squared Value	5,39	4,64	3,81
P-value	0,14	0,2	0,28

Table 56 - Results of Chi-squared test between movement-based signal signals and age clusters

H5: Neighbourhood of residence affects preferences for the signals categories (visuals, auditory and movement-based)

Method: Kruskal-Wallis

Outcome: Not Supported

Figure 46 shows the average score for the different signals' families, divided by neighbourhood.

- Visual signals are those with highest perceived effectiveness, followed by acoustic and for last the movement based.
- Rural clusters show a slightly higher score for visual signals and lower for acoustic and movement-based, compared to other clusters
- Overall, the behaviour of the three clusters is similar between one another

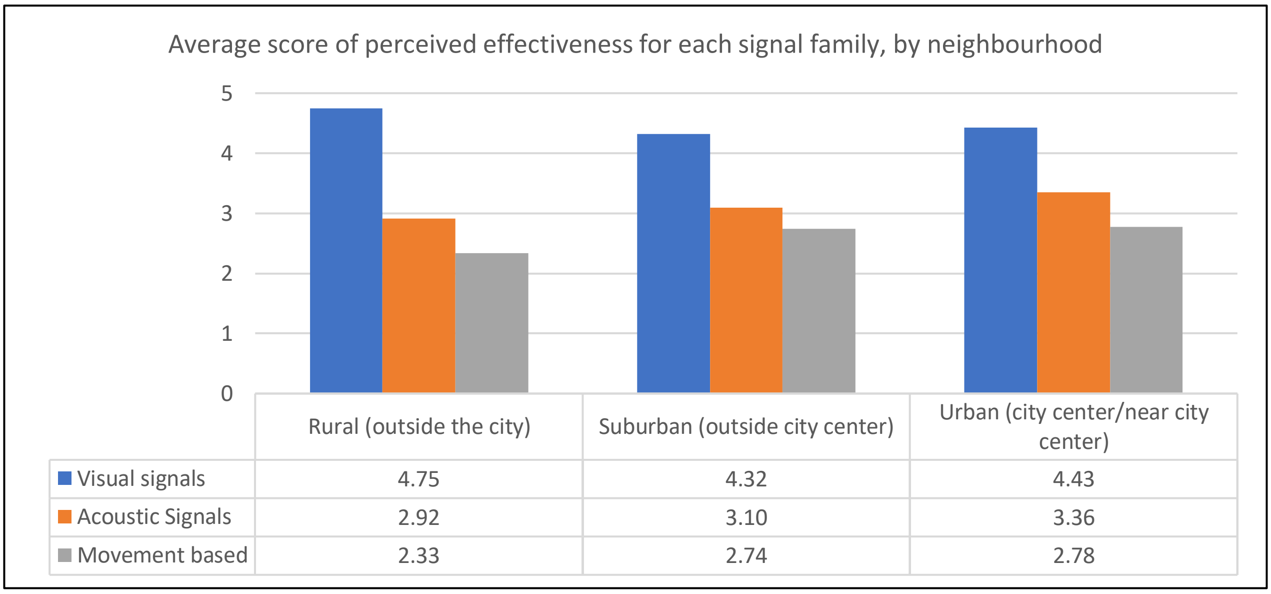


Figure 46

Table 57 show the outcome of the Kruskal-Wallis test. Results indicate that there is no influence of neighbourhood on the perceived effectiveness of signal categories.

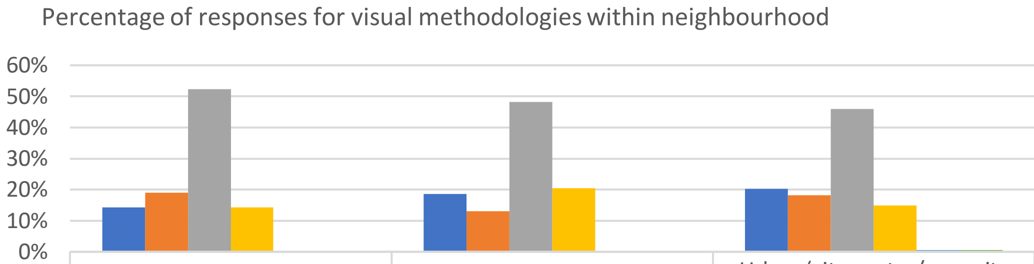
Categories	**Chi-Squared**	**P-value**
Visual Signals	2,54	0,28
Acoustic Signals	2,62	0,27
Movement based Signals	1,58	0,45

Table 57 – Results of Kruskal-Wallis test between signal categories and neighbourhood of residence

Additional analysis

It has been deemed appropriate to investigate also the possible influence of neighbourhood of residence on choice of signal signals.

Visual signals: According to Figure 47, rural areas show a slightly stronger preference for colours and text compared to other visual signals, while urban areas exhibit a balanced but slightly lower preference for colours compared to rural and suburban areas. Colours are the most chosen methodology across all neighbourhoods, suggesting they are widely perceived as effective visual signals.

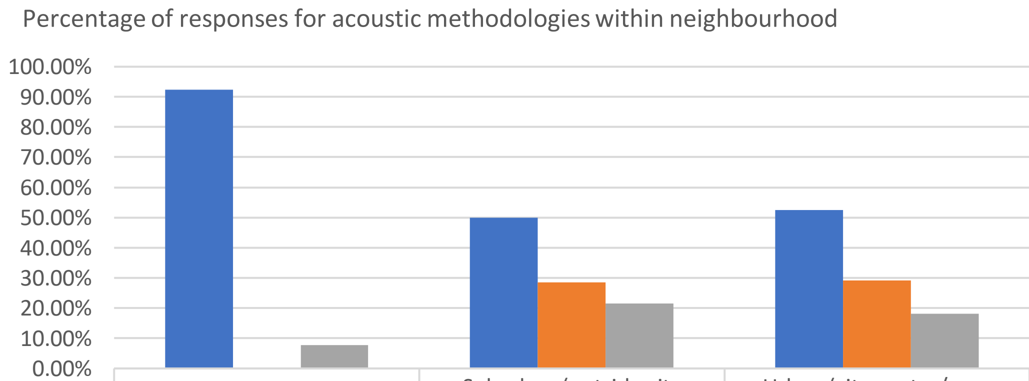


	Rural (outside the city)	Suburban (outside city center)	Urban (city center/near city center)
Images	14%	19%	20%
Text	19%	13%	18%
Colours	52%	48%	46%
Ground Projections	14%	20%	15%
Turn Signals	0%	0%	0%
Side Light	0%	0%	0%

Figure 47

Acoustic signals: Figure 48 shows that warning sounds are the most preferred acoustic methodology across all neighbourhoods, particularly in rural areas, where they dominate with over 90% preference, while the other two areas have moderate preferences for voice messages and musical tones, suggesting a m

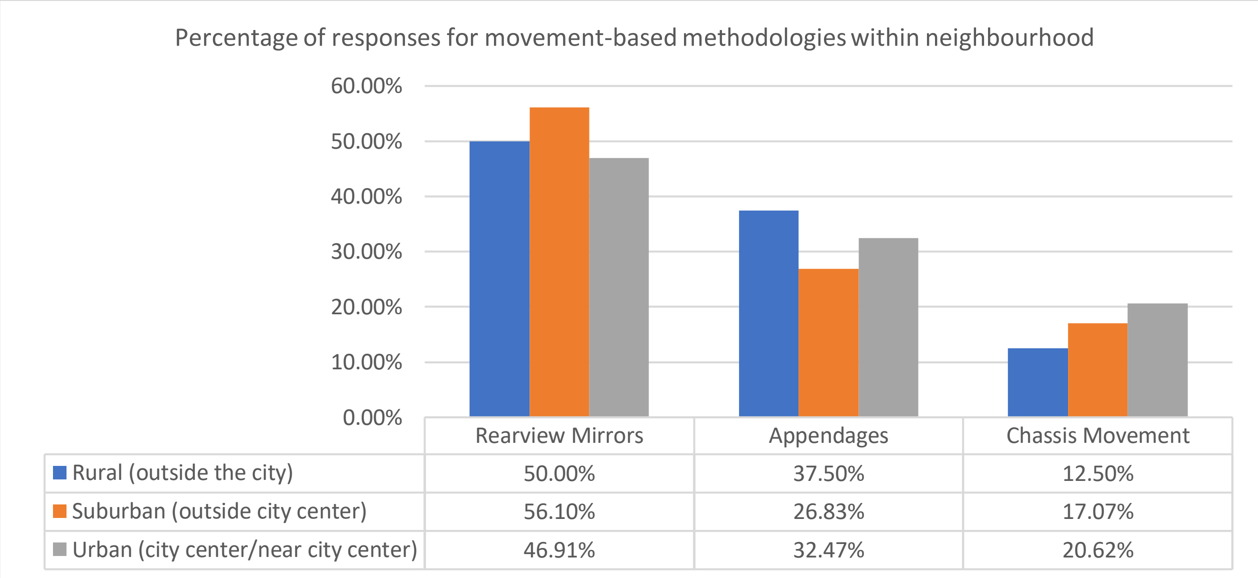
ore balanced reliance on diverse acoustic signals. Rural areas completely lack interest in voice messages (0%), possibly due to environmental or cultural factors favouring simpler auditory cues.



	Rural (outside the city)	Suburban (outside city center)	Urban (city center/near city center)
Sum of Warning_sounds	92.31%	50.00%	52.60%
Sum of Voice_message	0.00%	28.57%	29.17%
Sum of Musical_tones	7.69%	21.43%	18.23%

Figure 48

Movement-based signals: Figure 49 shows that across all neighbourhoods, review mirrors are consistently the most chosen method for movement-based signals, particularly in suburban areas. Rural areas favour appendages stronger compared to suburban and urban areas. Chassis movements are generally less preferred across all neighbourhoods but show slightly higher acceptance in urban settings.



	Rearview Mirrors	Appendages	Chassis Movement
Rural (outside the city)	50.00%	37.50%	12.50%
Suburban (outside city center)	56.10%	26.83%	17.07%
Urban (city center/near city center)	46.91%	32.47%	20.62%

Figure 49

The correlation it has been investigated through a Chi-squared test *(Table 58-59-60)*. The results indicate that neighbourhood of residence has an influence solely on the choice of *"Spoken Messages".*

VISUAL	**Images**	**Text**	**Colours**	**Projections on the ground**	**Turn signals**	**Side light**
Chi-squared Value	0,73	1,22	0,72	1,03	0,32	0,32
P-value	0,69	0,54	0,7	0,6	0,85	0,85

Table 58 – Results of Chi-squared test between visual signal signals and neighbourhood of residence

Acoustic	**Warning Sound**	**Musical Tones**	**Spoken Messages**
Chi-squared Value	4,9	2,09	8,03
P-value	0,09	0,35	1,7e-02

Table 59 - Results of Chi-squared test between acoustic signal signals and neighbourhood of residence

Movement based	Rearview Movement	Chassis Movement	Appendages Movement
Chi-squared Value	0,56	1,39	1,4
P-value	0,76	0,5	0,5

Table 60 - Results of Chi-squared test between movement-based signal signals and neighbourhood of residence

To understand the type of correlation, the table below shows the residual values of the Chi-squared test *(Table 61)*. Deviations for clusters "Suburban" and "Rural" are quite low, meaning that the answers' distribution is close to the expected values. For "Rural", deviation is wider, indicating that people of this cluster are way less likely to consider "Spoken messages" as their preferred method of communication

Spoken Messages	No	Yes
Rural	1,68	-2,14
Suburban	-0,04	0,04
Urban	-0,48	0,61

Table 61 – Residual values of Chi-squared test between "Spoken messages" and neighbourhood of residence

H6: Female pedestrians will report lower levels of perceived safety and trust (and consequently higher in worry and stress) in interactions with AVs compared to male pedestrians.

Method: Kruskal-Wallis

Outcome: Not Supported

Figure 50 shows the average for each emotion, clustered by gender. The differences between clusters are minimal, since the scores are similar for all the emotions. Only for confusion it can be noticed a slight increase in the score for female participants. Overall, the chart does not suggest the presence of a possible correlation between the variables.

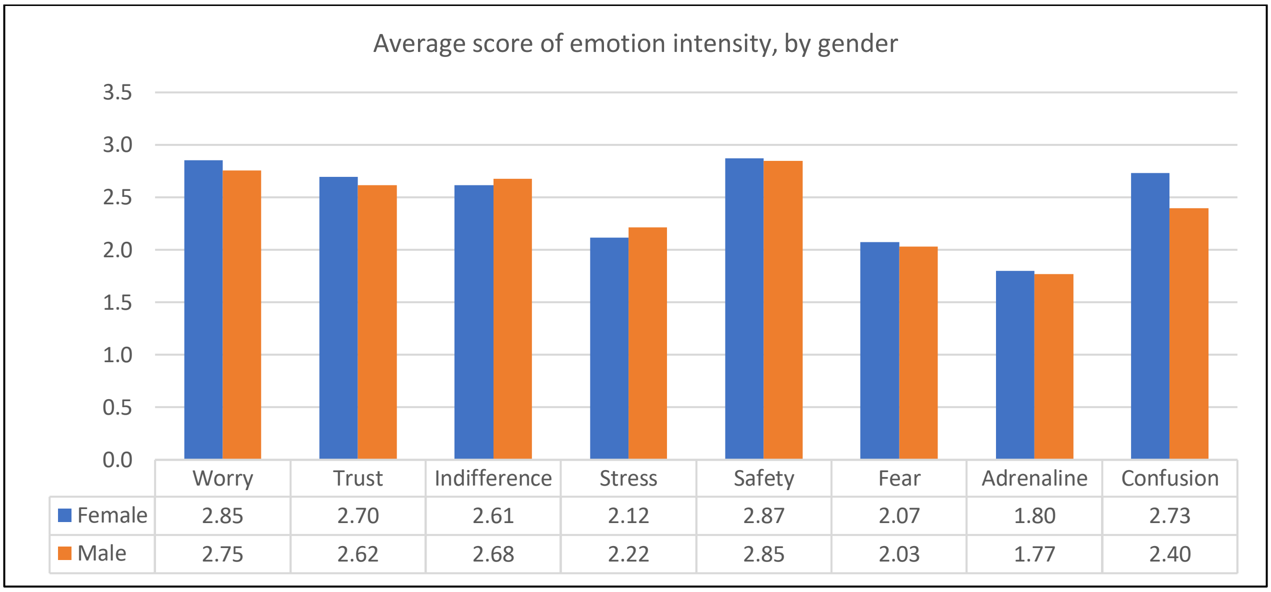


Figure 50

Table 62 shows the result of the Kruskal-Wallis test, indicating that, consistently with the preliminary insight, gender is not correlated with emotional responses of participants.

	Chi-squared	**P-value**
Worry	0,34	0,95
Trust	1,11	0,77
Indifference	1,12	0,77
Stress	0,45	0,93
Safety	0,97	0,81
Fear	0,49	0,82
Adrenaline	2,27	0,52
Confusion	3,99	0,26

Table 62 – Results of Kruskal-Wallis test between emotional responses and gender

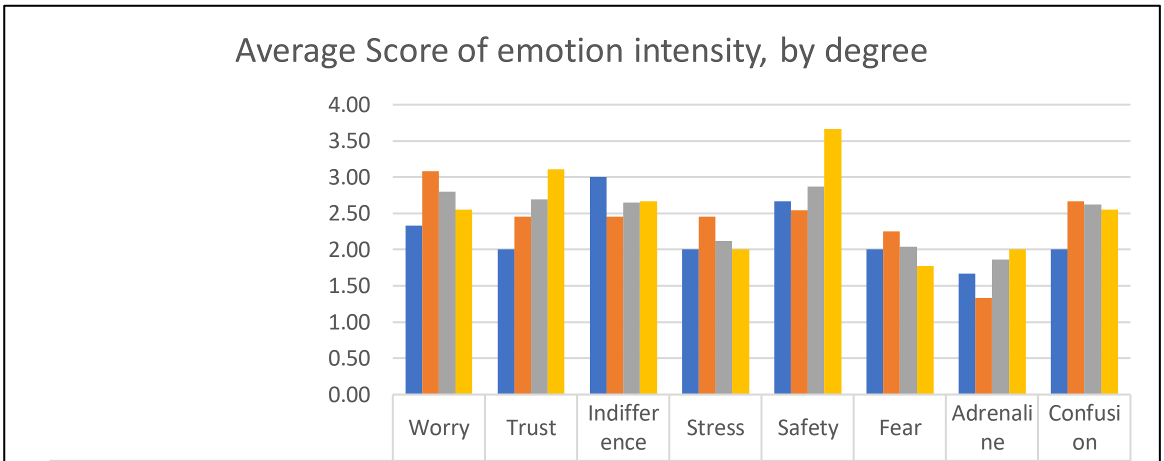
H7: Pedestrians with higher study degree are more likely to show more confidence (higher values of Trust and Safety) towards AV

Method: Kruskal-Wallis

Outcome: Not Supported

Figure 51 shows the Average score of emotion intensity, divided by study degree. From the chart following insight can be drawn:

- Trust and safety increase with education, particularly for those with a master’s degree or higher.
- Fear and worry tend to decrease as education levels rise.
- Indifference, stress, and confusion remain relatively stable across all groups.



	Worry	Trust	Indiffer ence	Stress	Safety	Fear	Adrenali ne	Confusi on
Less than a high school diploma	2.33	2.00	3.00	2.00	2.67	2.00	1.67	2.00
High school diploma	3.08	2.46	2.46	2.46	2.54	2.25	1.33	2.67
Bachelor's/Master's degree	2.80	2.70	2.65	2.12	2.87	2.04	1.87	2.62
Higher than a Master's degree	2.56	3.11	2.67	2.00	3.67	1.78	2.00	2.56

Figure 51

However, the results of the Kruskal-Wallis test *(Table 63)* do not support the insights, indicating instead the absence of correlation between study degree and emotional responses.

	Chi-squared	**P-value**
Worry	2,80	0,42
Trust	3,99	0,26
Indifference	1,18	0,76

Stress	2,87	0,41
Safety	5,69	0,13
Fear	1,37	0,41
Adrenaline	5,26	0,15
Confusion	1,10	0,80

Table 63 – Results of Kruskal-Wallis test between emotional responses and study degree

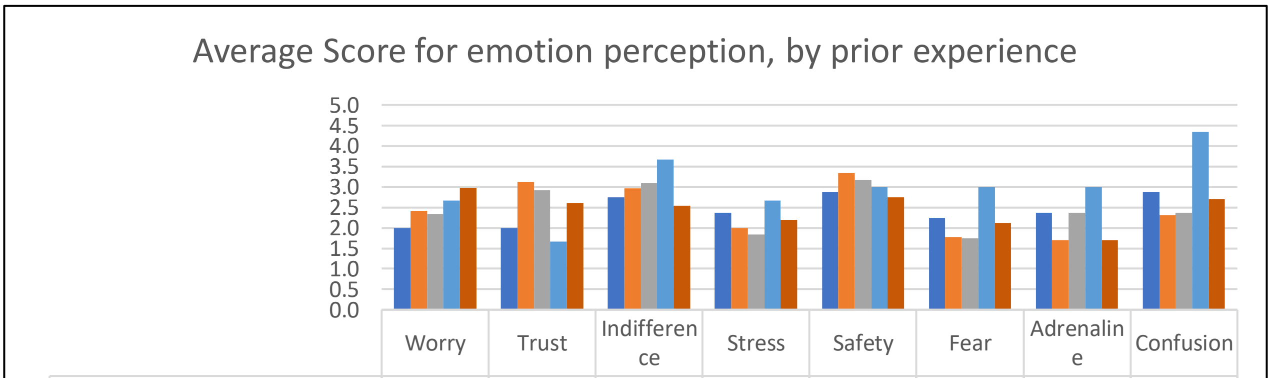
H8: Pedestrians with prior experience or interaction with AVs will report higher levels of perceived safety and trust when interacting with AVs compared to those with no prior experience.

Method: Linear Logistic Regression

Outcome: Supported

Figure 52 shows the average score for the different emotions, divided by prior experience with AVs:

- **Simulation experience** seems to have the most positive effect, increasing trust and safety while reducing negative emotions like worry and fear.
- **No experience** is associated with higher negative emotions (worry, fear, confusion) and lower trust and safety, indicating that prior exposure helps mitigate uncertainty.
- **Experience on road and outside** shows higher indifference and adrenaline scores, indicates slightly increased stress and worry compared to specific experiences.



	Worry	Trust	Indifference	Stress	Safety	Fear	Adrenaline	Confusion
Experience_inside_road	2.0	2.0	2.8	2.4	2.9	2.3	2.4	2.9
Experience_inside_simulation	2.4	3.1	3.0	2.0	3.3	1.8	1.7	2.3
Experience_outside	2.3	2.9	3.1	1.8	3.2	1.8	2.4	2.4
Experience_road_and_outside	2.7	1.7	3.7	2.7	3.0	3.0	3.0	4.3
No experience	3.0	2.6	2.5	2.2	2.7	2.1	1.7	2.7

Figure 72

Other combinations of experiences have been excluded from the analysis because of the very low number of respondents who have 2 or more type of experiences (Less than 4 respondents).

To check on statistical significance, a Linear Logistic Regression has been performed between the type of prior experience and the emotions. The results of Table 64-65 indicate that for trust and safety, only experience with a simulation appears to be significant, with a positive effect.

Surprisingly, experience with a simulation appears to be the only one significant being positively correlated (Value >0), instead of the experience on the road.

TRUST	**Value**	**P-value**
Experience from inside	-1,13	0,21
Experience on a simulation	0,86	2,6e-02
External experience	0,61	0,16
Experience from inside and outside	-1,57	0,28

Table 64 – Results of Logistic Linear Regression between "Trust" and prior experience with an AV

SAFETY	**Value**	**P-value**
Experience from inside	-0,36	0,69
Experience on a simulation	0,90	0,02
External experience	0,52	0,23
Experience from inside and outside	0,08	0,95

Table 65 – Results of Logistic Linear Regression between "Safety" and prior experience with an AV

Additional analysis

It has been deemed appropriate to check the correlation also with the other emotions in the scope of the research. According to the results of the Table from 66 to 71 fear, confusion worry, and adrenaline have been proved to be correlated to prior experience, while the other emotions are not. Surprisingly, experience on the road is significant only for worry, while for the other emotions experience on simulation is the crucial factor.

Single experiences tend to have positive effects (reducing intensity of negative emotions), while surprisingly the mixed experience, which is significative for fear, worry and confusion, tends to have a negative effect. This may be due to varied exposure leading to mixed perceptions.

WORRY	Value	P-value
Experience from inside	-2,49	7,63e-0,3
Experience on a simulation	-0,63	0,10
External experience	-0,99	0,02
Experience from inside and outside	3,13	0,02

Table 66 – Results of Logistic Linear Regression between "Worry" and prior experience with an AV

INDIFFERENCE	Value	P-value
Experience from inside	-0,52	0,46
Experience on a simulation	0,54	0,16
External experience	0,55	0,19
Experience from inside and outside	1,48	0,22

Table 67 – Results of Logistic Linear Regression between "Indifference" and prior experience with an AV

STRESS	Value	P-value
Experience from inside	0,14	0,85
Experience on a simulation	-0,46	0,27
External experience	-0,82	0,06
Experience from inside and outside	1,67	0,23

Table 68 – Results of Logistic Linear Regression between "Stress" and prior experience with an AV

CONFUSION	Value	P-value
Experience from inside	-0,92	0,21
Experience on a simulation	-0,49	0,2
External experience	-0,9	0,038
Experience from inside and outside	4,9	3,75e-04

Table 69 – Results of Logistic Linear Regression between "Confusion" and prior experience with an AV

FEAR	Value	P-value
Experience from inside	-0,43	0,61
Experience on a simulation	-0,91	3,46e-02
External experience	-1,04	1,97e-02
Experience from inside and outside	3,35	1,46e-02

Table 70 – Results of Logistic Linear Regression between "Fear" and prior experience with an AV

ADRENALINE	Value	P-value
Experience from inside	0,61	0,45
Experience on a simulation	-0,53	0,23
External experience	1,09	0,015
Experience from inside and outside	0,45	0,77

Table 71 – Results of Logistic Linear Regression between "Adrenaline" and prior experience with an AV

H9: As the size of the vehicle increases, so increase intensity levels for negative emotions (Worry, Stress, Confusion, Fear).

Method: Wilcoxon

Outcome: Supported

Figure 53 shows the difference in average of the scores for the intensity of the emotions as the size of the vehicles increases.

It can be noted that for negative emotions (Worry, Stress, Confusion, Fear) the difference is >0, meaning that the intensity tends to be higher as the size of the vehicle increases, while for positive emotions (Trust, Safety) difference is <0, meaning that people feel less secure at the increasing of the vehicle size. The only emotion that seems to be not influenced is Adrenaline.

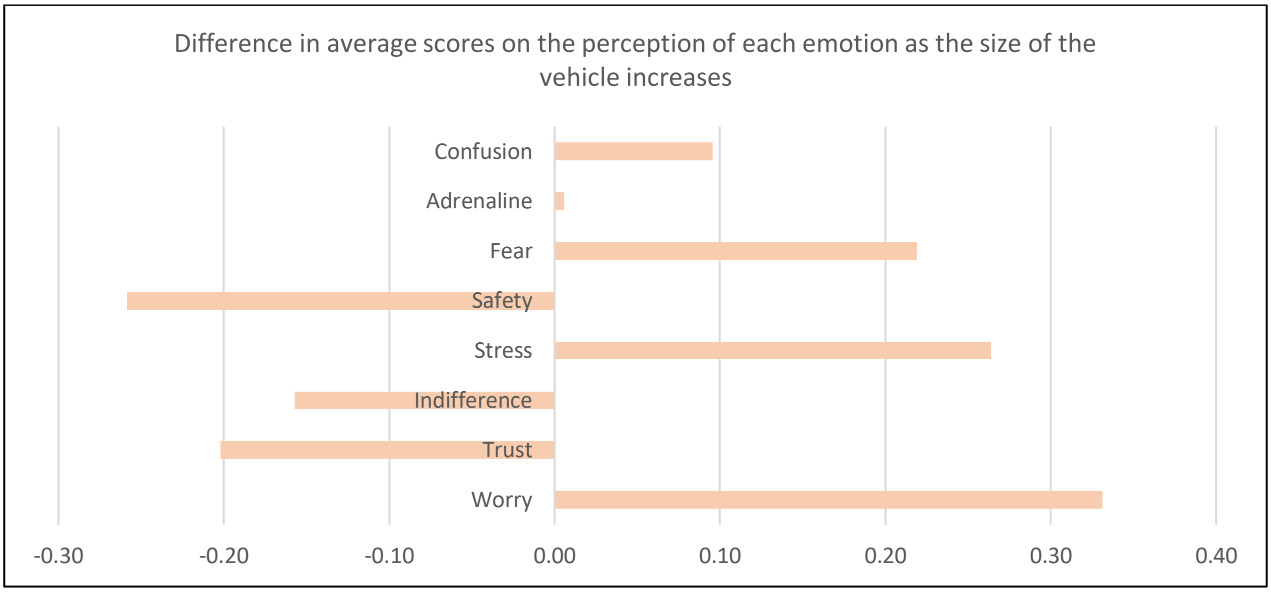


Figure 53

Overall, results are similar to those encountered for EVs. Through the Wilcoxon test the correlation it has been investigated *(Table 72)*. Similarly to EVs, size of the vehicle is a factor that influences most of the emotions in scope of this research. Those which are not impacted are confusion, indifference and adrenaline.

Emotions	P-value
Worry	3,33e-08
Stress	2,84e-06
Fear	4,80e-03
Confusion	0,07
Safety	5,37e-06
Trust	1,30e-0,3
Indifference	0,1
Adrenaline	0,94

Table 72 – P-values of Wilcoxon test on emotional responses

H10: Implementation of signals (visual, acoustic and Movement based) is positively correlated with positive emotions (Trust, Safety, Adrenaline) and negatively correlated with negative emotions (Fear, Stress, Worry, Confusion)

Method: Kendall's Tau

Outcome: Supported

The aim of the hypothesis is to understand how emotional responses change at the increase of perceived effectiveness of signal categories. To test the correlation between variables on Likert scale, it has been employed the Kendall's Tau Test to determine on which emotions the perceived effectiveness is significant. According to the results of Tables 73-74-75:

- Visual signals appear to be significant only in relation with trust, presenting a positive correlation (Tau >0).

	Worry	Trust	Indifference	Stress	Safety	Fear	Adrenaline	Confusion
Tau	0,07	0,14	0,65	-0,06	0,13	-0,08	0,01	0,06
P-Value	0,27	0,04	0,32	0,33	0,055	0,22	0,85	0,33

Table 73 – Results of Kendall's Tau test between emotional responses and perceived intensity of visual signal category

- Surprisingly, acoustic signals are not correlated with any of the emotions in scope.

	Worry	Trust	Indifference	Stress	Safety	Fear	Adrenaline	Confusion
Tau	0,02	0,05	-0,02	0,1	0,06	0,1	0,12	0,05
P-Value	0,73	0,4	0,79	0,12	0,3	0,12	0,06	0,46

Table 74 - Results of Kendall's Tau test between emotional responses and perceived intensity of acoustic signal category

- Movement-based signals are positively correlated with worry, even if the correlation is weak. All other emotions seem to be unimpacted.

	Worry	Trust	Indifference	Stress	Safety	Fear	Adrenaline	Confusion
Tau	0,14	-0,06	0,04	0,12	-0,04	0,11	0,1	0,08
P-Value	0,03	0,33	0,54	0,06	0,53	0,09	0,1	0,22

Table 75 - Results of Kendall's Tau test between emotional responses and perceived intensity of movement-based signal category

By looking at the occurrence's matrixes *(Figures 54-55)* it is possible to have a deeper understanding of the correlation that binds the variables. Following figures are the occurrences matrixes for the emotions that are influences by signals:

- **Visual:** Trust Levels 4 and 5 correspond predominantly to the highest visual signal effectiveness ratings (Levels 4-5), showing a strong positive relationship between the two. Specifically, the highest count (42 occurrences) is observed for Visual Signal Level 5 and Trust Level 2. This indicates that the perception of highly effective signals significantly boosts trust. Very few respondents report Trust Level 1, regardless of the perceived effectiveness of visual signals. This suggests that even minimally effective visual signals help to prevent very low trust levels.

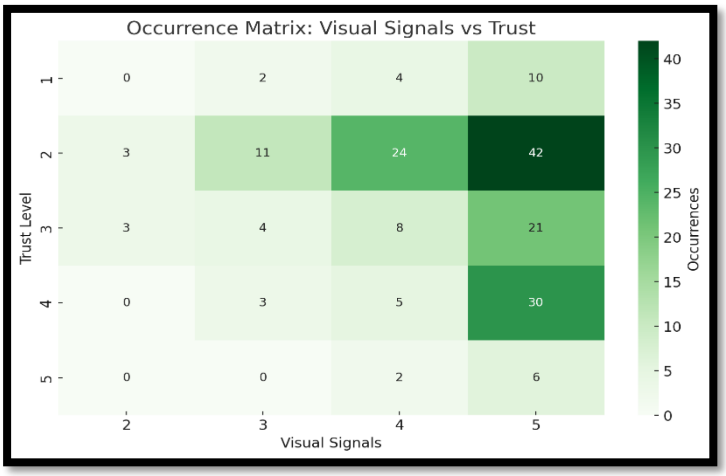


Figure 54

- **Movement based:** There is a clear trend that as the perceived effectiveness of movement-based signals increases, worry levels generally decrease. However, most responses for effectiveness are 2 and 3, meaning that generally the perceived effectiveness for these signals is low. The highest perceived effectiveness (Level 5) corresponds to lower worry levels. However, a very small number of respondents rated signals as highly effective.

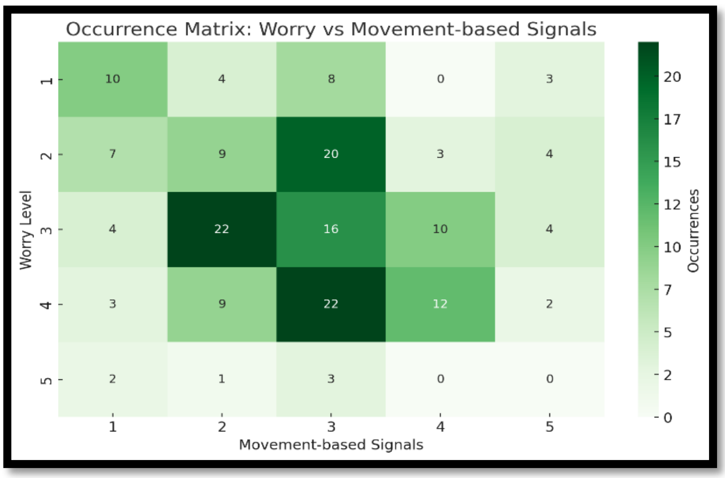


Figure 55

5.2.3. Discussion of Results

The findings contribute to a deeper understanding of the factors influencing the effectiveness of autonomous vehicle (AV) signal communication and pedestrian trust in AV technology. These results align with and expand upon existing literature, revealing that visual signals are consistently the preferred communication modality, while demographic variables play a nuanced role in shaping pedestrian interactions with AVs.

The study confirms that visual signals, particularly colour-coded eHMIs, are the most effective communication method for AVs. This aligns with previous research showing that pedestrians primarily rely on visual cues to interpret AV intent and movement (Faas & Baumann, 2021). Light-based eHMIs, such as LED strips or display panels, have been found to enhance pedestrian comprehension and increase perceived safety, a trend supported by recent findings on multimodal eHMIs (Dey et al., 2024).

While visual signals are dominant, acoustic signals rank second in effectiveness. This reflects prior research by Bazilinskyy et al. (2023), who emphasize the role of sound-based warnings in increasing pedestrian awareness, especially at night or in heavy traffic conditions. However, the study findings suggest that movement-based signals (e.g., vehicle tilting or adjusting its trajectory) are the least effective, which is consistent with previous literature indicating that such cues can be ambiguous and difficult to interpret quickly in real-world traffic situations (Zhao et al., 2024).

Demographic in Signal Preferences

While demographic factors do not significantly impact the overall preference for visual signals, they do influence specific modality preferences.

- Rural vs. Urban Differences:
  The study found that rural pedestrians exhibit lower trust in spoken auditory signals, which aligns with research suggesting that rural residents have less exposure to AV technology and are less familiar with voice-based vehicular communication cues (Rezvani et al., 2015). In contrast, urban pedestrians, who frequently interact with AV testing programs and smart infrastructure, report greater confidence in spoken eHMI signals, likely due to familiarity and technological adaptation (Rahman & Thill, 2023).
- Age-Based Variations:
  The study found that age does not significantly impact overall signal rankings; however, older pedestrians tend to prefer structured, highly visible visual signals over spoken messages or movement-based cues. This is supported by Faas & Baumann (2021), who found that older pedestrians struggle with auditory-based eHMIs and prefer predictable, colour-coded visual cues.
- Gender Differences in AV Trust and Interaction:
  While the study found that gender does not significantly influence emotional responses to AV interactions, prior research suggests that women tend to be more cautious and express greater safety concerns regarding AVs, especially in environments where visual or auditory cues are ambiguous (Tao et al., 2024).

Influence of Experience on Trust and Safety Perceptions

Prior exposure to AVs plays a critical role in shaping trust and safety perceptions. The study found that simulation-based experiences significantly improve pedestrian trust in AVs and reduce fear, while real-world exposure does not yield the same level of confidence. This aligns with previous literature, which highlights that controlled, structured AV interactions (such as VR-based simulations) can be more effective than spontaneous on-road encounters in building trust (Pires Abdullah & Sipos, 2024).

Interestingly, the study also found that repeated exposure to AVs does not produce cumulative emotional benefits, suggesting that a single, well-structured introduction to AV behavior may be as effective as multiple interactions. This supports findings by Zhao et al. (2024), who argue that familiarity with AV technology is a key determinant of trust, but that trust development plateaus after an initial period of adjustment.

The Psychological and Emotional Impact of AVs on Pedestrians

The study reveals that trust and stress levels are strongly influenced by the perceived risk associated with crossing in front of an AV. Pedestrians who view AVs as reliable and predictable report lower stress and fear levels, a finding that supports previous research on pedestrian comfort in AV interactions (Faas & Baumann, 2021).

Another critical determinant of pedestrian trust is driving experience. The study found that individuals who hold a driver's license exhibit lower fear levels and greater confidence when interacting with AVs. This is consistent with Rezvani et al. (2015), who found that understanding vehicular behaviour from a driver’s perspective reduces anxiety in AV interactions.

Vehicle Size as a Psychological Factor

A major finding of the study is that larger AVs evoke stronger negative emotions, such as fear and distrust, compared to smaller AVs. This aligns with literature showing that pedestrians perceive larger vehicles as more intimidating, leading to heightened caution (Faas & Baumann, 2021).

However, the study also indicates that despite stronger cognitive recognition of risk, larger AVs do not significantly increase physiological stress responses (e.g., adrenaline spikes). This suggests that while pedestrians consciously acknowledge the increased danger posed by larger AVs, their subconscious fear responses remain relatively stable. This finding is novel and warrants further investigation into how vehicle size influences pedestrian decision-making and behavioural adaptation in AV interactions.

Practical Implications for AV Design and Policy

One of the most important takeaways is the need for specific eHMI design that accounts for the varying preferences and trust levels among pedestrians. Visual signals, particularly colour-coded and light-based eHMIs, emerge as the most universally effective means of communication. Given that older pedestrians and individuals with limited AV exposure exhibit a preference for structured, high-contrast visual cues, AV manufacturers should prioritize universally recognizable LED indicators that clearly convey the vehicle’s intent. For urban settings, dynamic lighting systems, such as pulsating LED strips or surface projections on crosswalks, could further enhance the visibility and predictability of AVs. However, movement-based cues, which were ranked as the least effective in this study, should not be relied upon in isolation but rather supplemented with visual and auditory signals to improve their clarity.

Beyond the design of eHMIs, the study reinforces the importance of structured exposure programs in shaping pedestrian trust and safety perceptions. Simulation-based experiences have proven to be particularly effective in boosting confidence in AVs, suggesting that virtual reality (VR) and augmented reality (AR) technologies could play a pivotal role in public education. Municipalities and technology firms should collaborate to introduce VR-based pedestrian training modules that allow individuals to experience AV interactions in controlled settings. Similarly, interactive public demonstrations, where pedestrians can engage with AVs in controlled environments, could enhance familiarity and mitigate concerns about AV unpredictability. Public engagement efforts should also extend beyond urban centres, as the study highlights the pronounced scepticism towards AVs in rural areas. Lack of exposure, coupled with infrastructure limitations, contributes to hesitation among rural pedestrians, necessitating targeted outreach initiatives. Informational campaigns that address common misconceptions, combined with hands-on exposure to AV technology, could help bridge the acceptance gap between urban and rural communities

Urban infrastructure should also evolve alongside AV technology to facilitate safer interactions. The integration of smart crosswalks that communicate AV intentions through visual indicators could significantly improve pedestrian confidence. Similarly, dedicated AV-pedestrian interaction zones in high-footfall areas, where AVs adhere to stricter yielding protocols, may help ease concerns about AV unpredictability. In cities experimenting with large-scale AV deployment, redesigning intersections to accommodate AV-specific lanes or pedestrian-priority signals could further enhance safety and efficiency.

The emotional and psychological impact of AVs on pedestrians also warrants closer attention. The study reinforces prior research that larger AVs evoke stronger negative emotions, leading to increased hesitation and perceived risk. However, while pedestrians cognitively recognize the greater danger posed by larger vehicles, physiological stress responses such as adrenaline spikes appear not to escalate proportionally. This suggests that while pedestrians may be wary of AVs, their reactions remain measured and calculated rather than instinctively fearful. Nevertheless, AV designers should take these perceptions into account, perhaps by incorporating more pronounced safety signals in larger vehicles to reassure pedestrians of their intent.

6. Conclusions and Future Research

6.1. Conclusions

This research aimed to contribute to the existing literature on pedestrian interactions with autonomous and electric vehicles in crossing scenarios. A key focus was the role of eHMIs in facilitating clear communication, enhancing pedestrian trust, and promoting acceptance of these vehicles. Both AVs and EVs present challenges in pedestrian interaction, but their communication gaps differ significantly: EVs raise safety concerns due to their quietness, requiring artificial sound solutions to improve detectability during motion or manoeuvring, whereas AVs introduce uncertainty in pedestrian trust due to the absence of a human driver. Moreover, the adoption rates of AVs and EVs vary considerably across EU countries and globally, further justifying the need for separate analyses. Given these differences in both technological characteristics and diffusion, this study examined EVs and AVs separately to address their specific pedestrian interaction challenges more effectively.

Specifically, this research explored pedestrian preferences regarding different categories of communication signals, the role of emotions and human factors, and the influence of vehicle size on perceived safety for both EVs and AVs. These preferences were then analysed in relation to sociodemographic factors, providing a comprehensive understanding of methodologies to enable the pedestrians-vehicle communication and consequently the diffusion of such emerging mobility technologies.

The findings for electric vehicles highlighted a consistent trend: visual signals (such as colour-coded lights) emerged as the most clearly and positively perceived modality, offering pedestrians a heightened sense of clarity and reassurance. This preference is consistently observed across different age groups, neighbourhoods, and levels of formal education. Interestingly, an individual's primary mode of transport also influences their perceptions. For example, habitual walkers tend to prioritize visual and movement-based cues more than those who primarily drive.

. Another key finding concerns the perceived quietness of EVs. It is primarily pedestrians who already perceive EVs as unsafe that consider external alerts, including sounds, especially necessary for feeling secure. Across all these dimensions, prior experience proves to have a significant influence: individuals who have experience in riding in or interacting with EVs report to be more confident and less anxious about crossing the road in front of them. Furthermore, vehicle size also plays a significant role on perceptions: as the perceived bulk of an EV increases, participants' negative emotions (like worry or fear) tend to intensify, coupled with a decline in safety and trust.

A similar emphasis on visual signals characterizes the autonomous vehicle findings, where lights, screens, or projected cues consistently appear to foster the highest pedestrian confidence. In contrast to EVs, however, acoustic signals do not seem to significantly alter participants' emotions: people did not strongly connect specific sounds with a reduction in fear or worry. Furthermore, having prior direct experience with AVs, especially through controlled simulations, often translates into reduced wariness and greater trust. General demographic variables (age, gender, urban or rural background) do not systematically predict a pedestrian's readiness to embrace movement-based signals or, for that matter, how they respond to AVs on the street. Instead, familiarity with the technology consistently leads to more positive attitudes. In short, while autonomous vehicles share many of the same communication challenges seen with EVs, it appears that well-crafted visual interfaces and constructive exposure, particularly simulation-based, can substantially alleviate public concerns and provide a stronger sense of security in encounters with AVs. Even for AVs, vehicle size heightens negative emotions. Larger AVs evoke more apprehension especially in pedestrians that may instinctively hesitate when confronted with an imposing, driverless vehicle.

6.2. Limitations and Future Research

This study has provided useful insights into pedestrian interactions with AVs and EVs, however significant limitations must be acknowledged in order to interpret the findings.

First, the data was based only on self-reported replies obtained using a standardized questionnaire. While self-reported data is an effective method of obtaining subjective perceptions and attitudes, it is prone to bias. Participants' responses may have been influenced by recall bias, which is the inability to accurately recollect relevant past experiences, or social desirability bias, in which they altered their comments to comply with perceived expectations or norms. These factors may have caused disparities between participants' reported behaviours and their actual reactions in real-world situations.

In addition, the two questionnaires were administered to two different samples. The EV questionnaire was filled by only Italian participants, while the AV one did not have any geographic limitation. This may have nuanced the possible differences related to culture and demographics. Cultural factors tied to the country of residence can influence risk perceptions, trust in technological progress, and individual mobility habits. Such cultural variables make more challenging the direct comparisons between research carried out in different countries.

Moreover, this study evaluated three signal categories (visual, acoustic, and movement-based) to determine their usefulness in improving pedestrian safety and trust. While these categories are fundamental, they only cover a portion of the possible communication modalities. Future research could widen the scope by looking into additional signal kinds, such as haptic feedback or augmented reality systems, to gain a better understanding of their impact on pedestrian interactions.

Finally, the study's dependence on hypothetical circumstances presents a significant weakness. Participants did not have the opportunity to interact with AVs and EVs in real-world settings. This lack of direct, experiential interaction may have resulted in a mismatch between what participants expected and how they behaved when confronted with a moving vehicle in a real-world setting. The lack of situational reality may limit the findings' applicability to complex and unpredictable urban traffic conditions.

Recommendations for Future studies

Based on the results, several areas for future research emerge. Given the notably high effectiveness of visual signals in promoting trust and clarity, it is recommended to focus future investigations on deepening different forms of visual communication, such as colour-coded lights, ground projections, dynamic LED panels, or text-based and icon-based displays—and how they can be optimized for various pedestrian profiles. Field experiments in real urban and suburban settings could then assess how this variety of visual signals, alongside acoustic (continuous tones, voice messages, intermittent alerts) and movement-based cues (dynamic indicators, moving appendages), influences actual pedestrian behaviour, including reaction times and hesitation at crosswalks.

Furthermore, it is recommended to implement more structured forms of exposure to these vehicles: immersive training or gradual familiarization programs (for instance, VR experiences or live demonstrations) may help researchers examine how trust and perceived safety evolve across different demographics.
It would also be beneficial to analyse mobility habits and varying levels of digital or technological awareness among pedestrians, with a view to customizing signals for specific user needs and thereby enhancing overall safety and acceptance.
Finally, cultural variations may shape attitudes toward mobility and technology, complicating cross-national comparisons, thus calling for more in-depth local analyses and, where possible, tailored investigations that reflect socio-cultural, regulatory, and infrastructural differences.

7. Appendix

7.1. Questionnaire – EV (Translated in English)

This questionnaire has been distributed in Italian language. Here is the translated version in English.

Questionnaire on Interaction Between Pedestrians and Electric Vehicles

Section 1: Demographic Information

1. Age (years):
    - Under 18
    - 18-30
    - 31-45
    - 46-60
    - 61 and over
2. Gender:
    - Male
    - Female
    - Non-binary/Third gender
    - Prefer not to say
3. What is your highest level of education? (If you are a student, select the level you are currently attending):
    - Less than a high school diploma
    - High school diploma
    - Bachelor's/Master's degree
    - Higher than a Master's degree
4. In what type of neighbourhood do you live?
    - Urban (city centre/near city centre)
    - Suburban (outside city centre)
    - Rural (outside the city)
5. Do you have a driver's license?
    - Yes
    - No
6. What is the means of transport you use the most?
    - Car

- Motorcycle/Scooter
- Bicycle/Electric scooter
- Public transport
- Walking
- Other (please specify)

Section 2: Electric Vehicles with Traditional Driving

This section investigates preferences regarding communication methods between electric vehicles (EVs) and pedestrians. Electric vehicles are powered by rechargeable batteries, offering numerous advantages such as reducing greenhouse gas emissions and increasing energy efficiency. A distinguishing aspect of EVs is their quietness during operation, which, while improving urban quality of life, also presents unique challenges.

7. Have you ever experienced/interacted with an electric vehicle (EV)? (You may select multiple options):

   - ☐ Yes, I have driven an EV at least once
   - ☐ Yes, I have been a passenger in an EV but never a driver
   - ☐ Yes, I have seen an EV on the road
   - ☐ No, I have never had any experience with an EV
   - ☐ Other (please specify)

8. Do you consider the low noise of electric vehicles a possible safety problem?

   - Yes
   - No

9. Do you think crossing in front of electric vehicles is a safety problem?

   - Yes, always
   - Yes, only when the crossing is not regulated (e.g., absence of traffic lights)
   - No

10. On a scale from 1 to 5 (1 = not at all and 5 = very intense), how intense do you think the following emotions are when crossing the road/a junction in front of an electric vehicle?

	1	2	3	4	5
Worry					
Trust					
Indifference					
Stress					
Safety					
Fear					
Adrenaline					

Confusion					
Other (please specify)					

11. On a scale from 1 to 5 (1 = not at all and 5 = very intense), how intense do you think the following emotions are when crossing the road/a junction as the size of the electric vehicle increases (e.g., motorcycles, SUVs, buses, etc.)?

	1	2	3	4	5
Worry					
Trust					
Indifference					
Stress					
Safety					
Fear					
Adrenaline					
Confusion					
Other (please specify)					

12. On a scale from 1 to 5 (1 = not important at all and 5 = very important), how important do you think it is for an electric vehicle to communicate its actions and intentions (e.g., giving way, resuming motion, etc.) to pedestrians?

- 1
- 2
- 3
- 4
- 5

13. On a scale from 1 to 5 (1 = least effective and 5 = most effective), rate the following methods of communication to understand the intentions of an electric vehicle:

	1	2	3	4	5
Visual signals (e.g., lights, displays, text, colour changes on the chassis)					
Acoustic signals (e.g., sounds, voice messages)					
Movements of vehicle components (e.g., movement of dedicated flaps/appendages, rearview mirrors)					

14. Among visual signals, which types do you find most effective for understanding the intentions of an electric vehicle? (You may select multiple options):

- ☐ Coloured lights placed on the roof and/or side doors (e.g., green to give way, red to stop)
- ☐ Displays with text on the front hood
- ☐ Displays with animated images (e.g., arrows, symbols)
- ☐ Light projections on the ground (e.g., pedestrian crossing patterns)

- ☐ Other (please specify)

15. Among acoustic signals, which types do you find most effective for understanding the intentions of an electric vehicle? (You may select multiple options):

    - ☐ Warning sounds (e.g., alarm)
    - ☐ Voice messages (e.g., "I'm stopping," "Please, cross")
    - ☐ Musical tones
    - ☐ Other (please specify)

16. Among signals involving movements of vehicle components, which types do you find most effective for understanding the intentions of an electric vehicle? (You may select multiple options):

    - ☐ Movement of rearview mirrors
    - ☐ Movement of dedicated appendages
    - ☐ Change in the height of the vehicle's body relative to the road
    - ☐ Other (please specify)

7.2. Questionnaire - AV**Survey on Interaction Between Pedestrians and Autonomous Vehicles**

Section 1: Demographic Information

1. Age (years):
    Under 18
    18-30
    31-45
    46-60
    61 and over
2. Gender:
    Male
    Female
    Non-binary/Third gender
    Prefer not to say

3. Nationality:
[To be written in a text box here]
4. What is your highest level of education? (If you are a student, select the level you are currently attending):
    Less than a high school diploma
    High school diploma
    Bachelor's/Master's degree
    Higher than a Master's degree
5. In what type of neighborhood do you live?
    Urban (city center/near city center)
    Suburban (outside city center)
    Rural (outside the city)
6. Do you have a driver's license?
    Yes
    No
7. What is the means of transport you use the most?
    Car
    Motorcycle/Scooter
    Bicycle/Electric scooter
    Public transport
    Walking
    Other (please specify)

Section 2: Interaction with Autonomous Vehicles

This section aims to investigate preferences regarding communication methods between autonomous vehicles and pedestrians. Below is the definition of autonomous driving according to Sae International Standards:

Fully autonomous vehicles: These vehicles are fully autonomous and capable of performing all driving tasks under all conditions. They do not require any human intervention at any time. They can handle all types of roads and weather conditions autonomously; the vehicle is completely self-sufficient.

8. Have you ever experienced or interacted with an autonomous vehicle (AV)? (You may select multiple options)
   - ☐ Yes, I have experienced an AV on the road at least once
   - ☐ Yes, I have experienced an AV in a simulation at least once
   - ☐ Yes, I have seen AV on the road
   - ☐ Yes, I have seen an AV in a simulation
   - ☐ No, I have never had any experience with an AV
   - ☐ Other (please specify)
9. Do you think pedestrian crossing in front of autonomous vehicles is a problem in terms of safety?

   Yes, always

   Yes, only when the crossing is not regulated (absence of traffic lights)

   No
10. On a scale from 1 to 5 (1 = not at all and 5 = very intense), how intense do you think the following emotions are when crossing the road/a junction in front of an autonomous vehicle?

	1	2	3	4	5
Worry					
Trust					
Indifference					
Stress					
Safety					
Fear					
Adrenaline					
Confusion					
Other (please specify)					

11. On a scale from 1 to 5 (1 = not at all and 5 = very intense), how intense do you think the following emotions are when crossing the road/a junction as the size of the autonomous vehicle increases (e.g., motorcycles, SUVs, buses, etc.)?

	1	2	3	4	5
Worry					
Trust					
Indifference					
Stress					
Safety					

Fear					
Adrenaline					
Confusion					
Other (please specify)					

12. On a scale from 1 to 5 (1 = Not important at all and 5 = Very important), how important do you think it is for an autonomous vehicle to communicate its actions and intentions (e.g., giving way, resuming motion, etc.) to pedestrians?

 1
 2
 3
 4
 5

13. On a scale from 1 to 5 (1 = Least effective and 5 = Most effective), rate the following methods of communication to understand the intentions of an autonomous vehicle:

	1	2	3	4	5
Visual signals (e.g., lights, displays, text, colour changes on the chassis)					
Acoustic signals (e.g., sounds, voice messages)					
Movements of vehicle components (e.g., movement of dedicated flaps/appendages, rearview mirrors)					

14. Among visual signals, which types do you find most effective for understanding the intentions of an autonomous vehicle? (You may select multiple options)

- ☐ Coloured lights placed on the roof and/or side doors (e.g., green to give way, red to stop)
- ☐ Display with text positioned on the front hood of the car
- ☐ Display with animated images positioned on the front hood of the car (e.g., arrows, symbols)
- ☐ Light projections on the ground (e.g., pedestrian crossing patterns)
- ☐ Other (please specify)

15. Among acoustic signals, which types do you find most effective for understanding the intentions of an autonomous vehicle? (You may select multiple options)

- ☐ Warning sounds (e.g., alarm)
- ☐ Voice messages (e.g., "I'm stopping," "Please, cross")
- ☐ Musical tones
- ☐ Other (please specify)

16. Among signals involving movements of vehicle components, which types do you find most effective for understanding the intentions of an autonomous vehicle? (You may select multiple options)

- ☐ Movement of rearview mirrors
- ☐ Movement of dedicated appendages
- ☐ Change in the height of the vehicle's body relative to the road (e.g., lifting or lowering the vehicle)
- ☐ Other (please specify)

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