AutoTRUST

Autonomous self-adaptive services for TRansformational personalized inclUsivenesS and resilience in mobiliTy

D2.1 Best practices, users´ requirements and UCD methodology.v1

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Contents

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List of acronyms and abbreviations

Abbreviation	Description
AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application Programming Interface
ASR	Automatic Speech Recognition
AV	Autonomous Vehicle
CAV	Connected and Automated Vehicle
CNN	Convolutional Neural Network
DNN	Deep Neural Network
HCI	Human-Computer Interaction
iOS	iPhone Operating System
LLM	Large Language Model
ML	Machine Learning
NLP	Natural Language Processing
NLU	Natural Language Understanding
RAG	Retrieval-Augmented Generation
ReLU	Rectified Linear Unit
SDK	Software Development Kit
SNR	Signal-to-Noise Ratio
SoA	State-of-the-Art
SQL	Structured Query Language
STT	Speech-to-Text
TTS	Text-to-Speech
UCD	User-Centered Design
VA	Virtual Assistant
VAS	Virtual Assistant System
WP	Work package
xAI	Explainable Artificial Intelligence
V2X	Vehicle-to-Vehicle
RNN	Recurrent Neural Network
EKF	Extended Kalman Filter
FL	Federated Learning
CL	Cooperative Localization
ADAS	Advanced Driver Assistance Systems
ABS	Anti-lock Braking Systems
ESC	Electronic Stability Control
ACC	Adaptive Cruise Control
HE	Homomorphic Encryption

YOLO	You Only Look Once
SSD	Single Shot Detector
SORT	Simple Online and Realtime Tracking
MCNN	Multi-Column Convolutional Neural Network
C3D	Convolutional 3D Networks
VLMs	Vision-Language Models
CLIP	Contrastive Language-Image Pretraining
IVAQ	In-Vehicle Air Quality
PM	Particulate Matter
VOCs	Volatile Organic Compounds
CFD	Computational Fluid Dynamics
HMI	Human-Machine Interface
AR	Augmented reality
QoL	Quality Of Life
OECD	Organisation for Economic Co-operation and Development
PSR	Perceived Safety Risk
PPR	Perceived Privacy Risk
TAM	Technology Acceptance Model
PU	Perceived Usefulness
PEOU	Perceived Ease of Use
TPB	Theory of Planned Behaviour
TTC	Time-To-Collision
MTTC	Modified Time-To-Collision
ITS	Intelligent Transportation Systems
OSINT	Open-Source Intelligence
LSTM	Long Short-Term Memory
HRV	Heart Rate Variability
SCR	Skin Conductance Responses
HAD	Highly Automated Driving
IMU	Inertial Measurement Unit
GNSS	Global Navigation Satellite Systems

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Executive summary

This document outlines the foundational methodologies and best practices that guide the AutoTRUST project, which aims to design autonomous, personalized, inclusive, and resilient services for mobility. The document is structured to provide consortium members with key insights into user requirements and the UCD methodology, ensuring that the developed technologies address the diverse needs of end users. To achieve these objectives, the document outlines several critical components and methodologies, which are detailed as follows:

1. Key components include a review of the state-of-the-art technologies discussed in Section 2, such as sensor fusion, computer vision, natural language processing, and real-time data analytics, all of which are essential for the development of autonomous mobility solutions. These technologies enable multimodal processing, which is crucial for ensuring that Autonomous Vehicles (AVs) can interpret and respond to complex environments. The document also delves into the human factors involved in AV use, focusing on improving user interaction, safety, and trust in AV systems. Additionally, advanced monitoring systems are addressed, which play a critical role in tracking and optimizing AV performance, user behavior, and system reliability. The processes used to gather user requirements through focus group evaluations are also outlined, with the iterative design approach ensuring inclusivity and user satisfaction throughout the development of autonomous mobility technologies.
2. Moreover, the document specifies technical guidelines and architecture specifications, with a focus on flexibility and scalability for future-proof solutions. Specific Key Performance Indicators (KPIs) are outlined to assess the success of the project's outcomes in terms of reliability, user satisfaction, and ethical considerations.
3. The UCD methodology employed in the project places a strong emphasis on understanding users' cognitive, emotional, and social needs through direct engagement with stakeholders. This approach ensures that the final technologies are not only functional but also aligned with user expectations.

Through this approach, the AutoTRUST project seeks to develop AV systems that prioritize inclusiveness, trust, and safety, thereby contributing to the broader goals of enhancing the onboard experience and promoting resilient, user-friendly mobility solutions.

This first version of D2.1 (M6) describes the best practices, the users' requirements and the UCD methodology which is going to be put in practice in the project. Throughout the life of the project, we will refine and further update this report on M12 and M24. A final version is scheduled to be delivered on Month 36.

1. Introduction

Deliverable D2.1 “Best practices, users´ requirements and UCD methodology” is a document that provides guidelines for consortium members, outlining the user requirements, User-Centered Design (UCD) methodology, and the validation methods applied in the project. This document captures the initial steps undertaken, including a review of best practices, requirements gathering, and the establishment of a UCD methodology. Key activities covered include the state-of-the-art (SoA) analysis, selection of best practices, and the detailed definition of the system’s architecture and specifications. Additionally, the report describes the UCD methodology adopted to ensure that project outcomes align with diverse end-user needs. The study and specification of user- and system-level requirements, along with the definition of specific Key Performance Indicators (KPIs), are thoroughly discussed.

1.1. Purpose and structure of the document

The purpose of the AutoTRUST “Best practices, users 'requirements and UCD methodology” is to record the critical activities and decisions made during the initial stages of the AutoTRUST project, which are essential to its success. This report aims to describe the foundational activities that set the direction for the project, including a thorough review and selection of best practices identified through a comprehensive state-of-the-art analysis. These practices were chosen not only for their technical strengths but also for their alignment with the project’s goal of enhancing onboard experiences and promoting inclusiveness.

Beyond technical groundwork, this document emphasizes the methodologies used to understand and address user needs. It details the User-Centered Design (UCD) methodology central to AutoTRUST, illustrating how user requirements were identified and integrated into the design process. This includes a detailed description of a focus group session conducted with experts and stakeholders in the field, ensuring that the perspectives of diverse user groups, including those from minority and vulnerable populations, are considered in the development of pilot sites.

The report further articulates the architecture and system specifications defined collaboratively by project partners. These specifications not only serve as technical guidelines but also reflect a commitment to creating a flexible, extendable system architecture that can adapt to various hardware and software environments. This adaptability is critical to ensuring that the solutions developed within the project are both practical and future-proof.

Additionally, the document outlines the specific Key Performance Indicators (KPIs) established to measure the project's effectiveness and impact, covering factors such as reliability, performance efficiency, ethical considerations, and user satisfaction.

Following the Introduction, which sets the document's purpose, audience, and relevance within the project framework, the structure proceeds as follows:

Sections:

- **Section 2: State of the Art and Best Practices** – Reviews the current state-of-the-art technologies and best practices in autonomous mobility, covering key topics such as multimodal processing, cooperative 4D situational awareness, personalized adaptation, and human factors in autonomous vehicle (AV) design.
- **Section 3: User-Centered Design (UCD) Methodology** – Details the UCD methodology employed to ensure that user needs and experiences are central to the design of autonomous systems**.**
- **Section 4: Focus Group** – Outlines the evaluation protocol and structure for focus group sessions, including participant selection, feedback collection, and data analysis to guide the design of inclusive autonomous systems.
- **Section 5: Results** – Presents outcomes from the focus groups and other evaluations, summarizing key insights on user needs, safety concerns, and accessibility features that will shape the final AV system design.
- **Section 6: User Requirements and Guidelines** – Provides a comprehensive list of user requirements and guidelines derived from research and user feedback to guide the development of inclusive, comfortable, and safe AV systems.
- **Section 7: Challenges in the Development of Inclusive Autonomous Systems: The AutoTRUST Approach** – Describes challenges identified in the state-of-the-art review and how the AutoTRUST project plans to address them.
- **Section 8: Conclusion** – Concludes the document by reflecting on the project's strategic orientation and establishing expectations for upcoming milestones.

1.2. Intended Audience

The AutoTRUST "*Best Practices, User Requirements, and UCD Methodology*" deliverable is devised for public use as well as for the AutoTRUST consortium, comprising members, project partners, and affiliated stakeholders. This document serves as a comprehensive guide, providing detailed instructions on project requirements, the User-Centered Design (UCD) methodology, and validation methods used. It is designed as a reference tool to support consortium members throughout the project's duration.

1.3. Interrelations

The AutoTRUST consortium integrates a multidisciplinary spectrum of competencies and resources from academia, industry, and research sectors, focusing on novel AI-leveraged self-adaptive framework for transformational personalized inclusiveness and resilience in CCAM. The project integrates a collaboration of sixteen partners from ten EU member states and associated countries (Norway, Switzerland, United Kingdom, Korea and Japan), ensuring a broad representation for addressing security, privacy, well-being, health, and assistance, leading to enhanced inclusiveness, trust, and safety in the interaction between users and automated vehicles.

AutoTRUST is categorized as a "Research Innovation Action - RIA" project and is methodically segmented into 6 WPs, further subdivided into tasks. With partners contributing to multiple activities across various WPs, the structure ensures clarity in responsibilities and optimizes the communication amongst the consortium's partners, boards, and committees. The interrelation framework within AutoTRUST offers smooth operation and collaborative innovation across the consortium, ensuring the interconnection of the diverse expertise from the various entities (i.e., Research Institutes, Universities, SMEs, and large industries). The “Best practices, users 'requirements and UCD methodology” addresses all activities of the AutoTRUST project related to state-of-the-art analysis, as well as the relevant user requirements through UCD methodology, in order to form the basis for the design procedures within WP2 and provide also input to technical WPs, such as WP3 and WP4. Moreover, it will facilitate the evaluation procedures in WP5.

2. State of the Art and best practices

This section provides a general overview of the main research directions and best practices for the solutions for inclusive and user-friendly mobility for leisure, commuting and, more generally, socialisation that is independent of the type of vehicles, passengers, and reason of mobility.

2.1. Multimodal processing and Advanced Monitoring System (AMS)

2.1.1. Cooperative 4D situational awareness

Autonomous vehicles (AVs) employ a variety of sensors such as cameras, LiDAR, GNSS (global navigation satellite systems), and IMUs (inertial measurement units) to perceive and interpret their environment. These vehicles are expected to be a fundamental component of future Intelligent Transportation Systems [1]. Moreover, vehicles enhance their perception capabilities beyond the individual sensor range through Vehicle-to-Vehicle (V2X) communication and 5G, allowing them to share crucial traffic information. Achieving precise 3D location awareness over time is essential for optimizing autonomous driving performance. A promising approach for enhancing location or situational awareness is to exploit collaboration among vehicles, either during training or the decision-making phase, relying on V2X information exchange [2], [3]. This approach becomes even more effective when the uncertainty of sensor measurements can be estimated using data-driven or deep learning techniques [4]. KalmanNet [5], a Recurrent Neural Network (RNN) designed to estimate the uncertainty for a single agent through the principles of the Extended Kalman filter (EKF), is considered as a state-of-the-art approach, exactly due to its interpretability and efficiency in capturing unknown system dynamics.

Collaboration during training usually refers to a distributed scenario where clients jointly train models used for localization applications, using their own local models. In this Federated Learning (FL) scenario, a global server aggregates the local models and sends back to the clients the global model after some communication rounds [6], [7]. FedLoc [8], [9] is a very popular generic framework, focusing mainly on indoor localization scenarios of edge devices. However, despite its benefits, it requires extensive trainable parameters and large datasets, even for simple sequences, lacking the explainability of KalmanNet. Indoor localization based on WiFi measurements is also the focus of related FL works [10][11]. Collaboration during the decision-making phase, usually refers to Cooperative Localization (CL) based on traditional optimization techniques. Understanding the statistics of measurement noise is crucial for enhancing location estimation accuracy [2]. Centralized methods, such as those using multidimensional scaling [12] or quadratically constrained quadratic problems [13], often either assume the noise covariance is known in advance or set it equal to the identity matrix. More practical distributed approaches, which utilize the concept of covariance intersection [14],[15], typically assume the true covariance matrices are known, without addressing how they can be estimated in practice. However, in all cases CL requires raw data exchange in order to localize vehicles, thus resulting in high communication costs and privacy issues.

Thus, the main challenge addressed is to design an explainable data-driven localization architecture that utilize the collaborative nature of FL in order to enhance Avs localization, and as a matter of fact, 4D situational awareness.

2.1.2. Multi-agent path planning for tackling motion sickness and improving comfort

Connected Advanced Driver Assistance Systems (ADAS) help to reduce road fatalities and have received considerable attention in the research and industrial societies [16]. Recently, there is a shift of focus from individual drive-assist technologies like power steering, anti-lock braking systems (ABS), electronic stability control (ESC), adaptive cruise control (ACC) to features with a higher level of autonomy like collision avoidance, crash mitigation, autonomous drive and platooning. More importantly, grouping vehicles into platoons [17], [18] has received considerable interest, since it seems to be a promising strategy for efficient traffic management and road transportation, offering several benefits in highway and urban driving scenarios related to road safety, highway utility and fuel economy. To maintain the cooperative motion of vehicles in a platoon, the vehicles exchange their information with the neighbours using V2V and V2I [19]. The advances in V2X communication technology [18], [19] enable multiple automated vehicles to communicate with one another, exchanging sensor data, vehicle control parameters and visually detected objects facilitating the so-called 4D cooperative awareness (e.g., identification/detection of occluded pedestrian, cyclists or vehicles). Several works have been proposed for tackling the problems of cooperative path planning. Many of them focus on providing spacing policies schemes using both centralized and decentralized model predictive controllers. Though very few take into account the effect of network delays, which are inevitable and can deteriorate significantly the performance of distributed controllers. The authors in [20], presented a unified approach to cooperative path-planning using Nonlinear Model Predictive Control with soft constraints at the planning layer. The framework additionally accounts for the planned trajectories of other cooperating vehicles ensuring collision avoidance requirements.

Similarly, a multi-vehicle cooperative control system is proposed in [21], [22] with a decentralized control structure, allowing each automated vehicle to conduct path planning and motion control separately. The authors in [17] present a robust decentralised state-feedback controller in the discrete-time domain for vehicle platoons, considering identical vehicle dynamics with undirected topologies. An extensive study of their performance under random packet drop scenarios is also provided, highlighting their robustness in such conditions. The authors in [23] have extended decentralized MPC schemes to incorporate also the predicted trajectories of human driving vehicles. Such solutions are expected to enable the co-existence of vehicles supporting various levels of autonomy, ranging from L0 (manual operation) to L5 (fully autonomous operation) [24]. Furthermore, a distributed motion planning approach based on artificial potential field is proposed in [25], where its innovation is related to developing an effective mechanism for safe autonomous overtaking when the platoon consists of autonomous and human-operated vehicles. Additionally, to the cooperative path planning mechanisms, spacing policies and controllers have also received increased interest towards ensuring collision avoidance by regulating the speeds of the vehicles forming a platoon. Two different types of spacing policies can be found in the literature, i.e., the constant-spacing policy [26][27] and the constant-time-headway spacing policy (e.g., focusing on maintaining a time gap between vehicles in a platoon resulting in spaces that increase with velocity) [1]. In both categories, most works, use a one direction control strategy. At this point, it should be mentioned that in a one-directional strategy the vehicle controller processes the measurements which are received from leading vehicles. Similarly, a bidirectional platoon control scheme takes into consideration the state of vehicles in front and behind (see [28]) . In most of the cooperative platooning approaches, the vehicle platoons are formulated as double-integrator systems that deploy decentralised bidirectional control strategies similar to mass–spring–damper systems. This model is widely deployed since it is capable of characterising the interaction of the vehicles with uncertain environments and thus is more efficient in stabilising the vehicle platoon system in the presence of modelling errors and measurement noise. Though, it should be noted that the effect of network delays on the performance of such systems, has not been extensively studied, despite the fact that time delays, including sensor detective delay, braking delay and fuel delay not only seems to be inevitable but also is expected to deteriorate significantly the performance of the distributed controllers.

2.1.3. Trustworthy and dynamically adaptable intelligence via continual federated learning

The recent rapid increase of interest for machine learning methods and the associated requirement for utilizing training datasets of immense size, have driven the quest for research in collaborative machine learning schemes [29]. The general idea of this concept is that a number of computing entities, hereafter also termed as agents, cooperate via a network with the scope to train a common, complex machine learning model. Thus, the data required for training can be split among the cooperating agents, relaxing the memory and computation requirements of each agent and enabling the training of more elaborate models. One recent and successful protocol for collaborative machine learning has become known as [30].

In this context, FL has emerged as an ML paradigm that enables collaborative model training while retaining the original personal data of the end-users, thereby suppressing privacy-related risks, since only parameters are exchanged for model aggregation and updates, and not the data themselves. In the conventional FL, referred to as unimodal FL the local data of agents stem from a single modality.

The distributed setting for federated optimization is formulated as:

$$f(w) = \frac{1}{n}\sum_{k=1}^{K} n_k F_k(w)$$

where the local empirical loss function $F_k(w)$ is defined as:

$$F_k(w) = \sum_{i \in P_k} f_i(w)$$

with $f_i(w)$ being a loss function. Here, K is the number of local nodes, P_k is the training dataset of node k = {1..K}, with size $n_k = |P_k|$. Without loss of generality, FL unfolds over several rounds and typically includes these key steps:

1. Local Model Optimization: Each client optimizes its local model utilizing a private dataset.
2. Fusion at server: The clients send their individually updated models to the central server. The server then combines these models using a specific aggregation method to form a global model.
3. Global Model Distribution: The server disseminates this updated global model back to the agents, paving the way for the subsequent round.

In the FL framework various challenges emerge due to the complex nature of the involved clients such as statistical heterogeneity, communication load and privacy concerns.

Statistical heterogeneity in autonomous driving scenarios applications occurs when diverse datasets across clients, like edge devices or nodes, deviate from the IID assumption. This heterogeneity, or non-IID nature of data, can adversely affect the performance of FL models. In such scenarios, the local data distribution at each client diverges significantly from the overall global data distribution. Consequently, when local models trained on these diverse datasets and are aggregated to form a global model, the result may not accurately reflect the outcome of a model trained on a centralized dataset (where all local datasets are combined). In response to these challenges posed by non-IID data, numerous studies in the literature focus on developing strategies and techniques to address these discrepancies that mainly revolve around the idea of Personalized Federated Learning. In such case, the focus is on creating individualized models for each client, taking into account the heterogeneity of their data and adapting to the diverse data distributions of each client.

Personalized FL can be implemented in various ways and is typically categorized based on whether the personalization takes place on the server or the clients [31]. In the former case the global model is the result of a two-step approach: FL training and local fine tuning. This strategy aims to improve the global model's performance under data heterogeneity to enhance subsequent personalization on local data. The techniques under this category can be classified into data-based and model-based approaches. Data-based methods mitigate client drift by reducing statistical heterogeneity among clients' datasets by augmenting data [32][33]. Model-based approaches focus on learning a robust global model or improving local model adaptation performance employing techniques, like regularizing models for preventing overfitting [34] or transfer learning techniques, like domain adaption where the training also involves creating personalized models by fine tuning the local model [35]. The latter personalization approach targets at training individual personalized models instead of a single global model. It modifies the FL model aggregation process using different learning paradigms. The techniques in this category aim to create a personalized model for each client through methods such as parameter decoupling [36], in which each client is allowed to contain some personalized layers in the deep learning models focused on the local data distribution of the client, clustering where client's relationships are utilized to generate personalized models for related clients [32].

Apart from the challenges posed by non-IID data distributions, deploying FL in real-world situations faces two other critical challenges. Firstly, there's a significant communication load between the server and the edge devices. Secondly, the devices exhibit a wide range of computational and power capabilities.

Communication Load: In real-world environments, the limited computational and communication capacities of devices necessitate the use of smaller and less resource-intensive neural networks [37]. This limitation can significantly influence the performance of the trained models. Efforts to improve communication efficiency in FL have led to the exploration of various methods such as compression techniques (like sparsification and quantization) and selective client engagement [38]. Nonetheless, these methods may sometimes reduce model accuracy or introduce biases towards certain devices.

Heterogeneous Computing Capabilities: Also, focusing on the hardware heterogeneity of the devices, one straightforward approach is to select only clients with adequate computational resources, while disregarding those with limited hardware, which may still possess valuable information. Alternatively, a model architecture could be employed to fit the minimum capabilities of all clients, but this may constrain the overall representation ability of the global model [39]. Another direction relies on deploying different models across clients adapted to their computational resources. To exchange information over heterogeneous models the knowledge distillation technique is applied to enhance the global model with an ensemble of local predictions [40]. However, implementing such approaches can be challenging due to the complex aggregation rules required on the server or the need for clients to share a public proxy dataset, which may not be feasible for devices with limited memory [6].

Security concerns: Furthermore, in the conventional FL setup, client models are often transmitted openly, posing significant privacy and confidentiality risks, particularly with sensitive data susceptible to reverse engineering attacks like Gradient Leakage. To address these concerns, various privacy-enhancing techniques such as gradient leakage-resilient methods and data encryption have been developed. However, these solutions may compromise model performance. Alternative approaches, including Multi-party Computation and Homomorphic Encryption (HE), offer promising privacy preservation by enabling computations on encrypted data, producing encrypted outcomes [7]. This allows for secure model aggregation in FL without exposing the models themselves. Yet, aggregating encrypted data from multiple sources necessitates a shared encryption key.

Multi-agent vehicular systems must cope with:

- multi-variate and dynamic scenarios, which involve corner cases of rare but critical in nature events (e.g., car accidents in automotive applications [41]),
- privacy considerations due to the required information exchange [42], and
- data biases.

To address these challenges, a lifelong multi-stage training that updates model parameters via FL [43] can be an attractive approach to follow. Additionally, in real-world settings and applications, the local datasets of the participating vehicles are often heterogeneous especially in time- and space-varying conditions, deteriorating the rate convergence, due to the so-called non-IID data [44].

2.1.4. Holistic Visual Analysis

Rather than relying on individual tasks like object detection, semantic segmentation, or instance segmentation in isolation, the holistic visual analysis builds upon advancements in deep learning, particularly through the use of large-scale pre-trained models, transformers, self-supervised learning, and multimodal approaches to provide better performance [49]. Recent state-of-the-art models aim to address multiple tasks simultaneously, instead of task-specific architectures. These architectures are designed to perform multiple related tasks (like object detection, segmentation, and pose estimation) from a shared representation. To design these architectures powerful base models are often combined. Some example base models include the following:

Object Detection Algorithms

- YOLO (You Only Look Once) [50] is a real-time object detection algorithm that can detect passengers entering and exiting the bus by identifying humans in camera footage. It is fast and can operate in real-time, making it ideal for continuous monitoring.
- SSD (Single Shot Detector) [51] is another real-time object detection algorithm that can detect and count passengers based on live video streams. It is slightly slower than YOLO but still effective in tracking people.
- DETR [51] introduced the concept of leveraging transformers for object detection, extending its approach to tasks like segmentation and tracking. The **Mask2Former** model builds upon this by combining mask-based and transformer-based approaches to achieve holistic segmentation.

Human Pose Estimation Algorithms

- OpenPose [53] detects the human skeleton and keypoints in real-time. It can help track individual passengers' movements, ensuring passenger safety while boarding and alighting. This can be useful to prevent accidents and improve safety, such as ensuring passengers are seated before the bus starts moving.

- AlphaPose [54] offers more accurate and detailed human pose estimations and is useful in crowded vehicle scenarios where multiple people need to be tracked simultaneously.

Tracking Algorithms

- SORT (Simple Online and Realtime Tracking) [55] is a lightweight tracking algorithm that can be used in conjunction with detection models like YOLO or SSD to track passengers as they move around the bus. It can monitor how passengers board, alight, or move within the bus, ensuring no overcrowding or safety hazards.
- DeepSORT [56] is an improved version of SORT that integrates appearance-based features for more robust tracking. It helps track individual passengers even when they are temporarily occluded.

Crowd Counting and Density Estimation

- CSRNet [57] is a neural network architecture specifically designed for crowd counting. It can estimate the number of passengers in the bus, even in crowded conditions. This helps monitor overcrowding in buses and ensures adherence to capacity limits.
- MCNN (Multi-Column Convolutional Neural Network) [58] can estimate the density of people in crowded scenes. It can be used to gauge how many passengers are currently in a vehicle and optimize the operation of the bus based on real-time data.

Gesture and Action Recognition

- C3D (Convolutional 3D Networks) [59] are used for action recognition in video footage and can monitor specific behaviours, such as passengers signaling for a stop or standing up before the bus halts.

Semantic Segmentation

- DeepLab [60] can be used to segment the video footage and distinguish between passengers, bus seats, doors, and other objects. This can help in more accurate monitoring and detection of where passengers are located inside the bus.
- U-Net [61] can be used for pixel-wise segmentation of passengers in different areas of the bus, helping to monitor occupancy and ensure safety protocols (e.g., not allowing passengers to stand in restricted areas).

Multi-modal foundation models

- Vision-Language Models (VLMs) [62]: Approaches like CLIP, ALIGN, DALL·E, and **Flamingo** have demonstrated the power of combining visual and linguistic information. This allows models to perform more comprehensive tasks that require understanding both image content and associated text (such as captioning, VQA, and image generation). CLIP (Contrastive Language-Image Pretraining) from OpenAI, a notable example, aligns image and text representations, allowing for cross-modal learning. These models can perform zero-shot classification, object recognition, and image generation, showing potential for holistic visual reasoning in multi-task settings.

- YOLO-world [63]: YOLO-World is pre-trained on large-scale datasets, including detection, grounding, and image-text datasets. YOLO-World is the next-generation YOLO detector, with a strong open-vocabulary detection capability and grounding ability. YOLO-World presents a prompt-then-detect paradigm for efficient user-vocabulary inference, which re-parameterizes vocabulary embeddings as parameters into the model and achieve superior inference speed.

Optical Flow for Movement Detection

Optical flow techniques like Farneback Optical Flow [64] can detect the movement patterns of passengers within the bus. This is useful for understanding passenger behavior, such as identifying areas where passengers tend to crowd or bottlenecks during boarding and alighting.

Each of these algorithms can be deployed using a camera system installed in the vehicle to analyze the footage in real-time or post-processed for operational insights. By combining such modules, it is possible to develop holistic visual understanding models that can facilitate the following:

- Development of an integrated, lightweight model that combines object detection (YOLO), tracking (DeepSORT), and anomaly detection in a single pipeline. This reduces the need for separate models, minimizing computational overhead while maintaining accuracy.
- Development of a smart system that monitors passengers' safety by analyzing both individual behaviours and crowd dynamics inside the bus in real-time. Through a real-time safety protocol, the system can send alerts to the driver or central control if unsafe actions are detected. By optimizing pose estimation and action recognition models, the system would prioritize efficiency and accuracy in resource-constrained hardware.
- Create an adaptive system that tracks the flow of passengers, predicts bottlenecks, and alerts drivers or the central system about overcrowded areas within the vehicle. Development of a predictive system that adjusts bus operations dynamically (e.g., opening additional doors or adjusting bus speed) to manage crowding in real-time. By using

lightweight detection and crowd counting models, the system will minimize computational demands.

- Implementation of a real-time gesture recognition system that identifies specific gestures from passengers, allowing for improved interaction with bus services (e.g., requesting a stop) or detecting emergency signals. The system could be optimized for edge devices through model pruning and can work without requiring large-scale GPUs, making it deployable on low-power devices.

2.1.5. In-vehicle air-quality and thermal comfort analysis

Among the most important factors directly affecting the comfort, health, and safety of a vehicle's passengers are in-vehicle air quality (IVAQ) and thermal comfort conditions [65]. IVAQ is influenced by various external and internal sources of pollutants that can be harmful to passengers [66][67]. External sources include vehicle emissions, which may release pollutants such as carbon monoxide and particulate matter (PM) [68]. Internal sources, such as materials used in the vehicle's cabin—like carpets, plastics, and adhesives—can emit volatile organic compounds (VOCs) [69]. Thermal comfort, in contrast, primarily refers to the temperature distribution inside the vehicle's cabin, which can lead to discomfort if it becomes excessively warm or cold for the passengers [70].

Monitoring, reporting, and analyzing both IVAQ and thermal comfort conditions can be achieved through the installation of smart equipment inside the cabin for real-time data measurement or by using numerical models. Smart equipment includes air quality sensors that can be fixed located and can measure temperature, humidity, VOCs, and PM in real-time [71][72]. These sensors are then connected to a software platform, used for data processing, visualization, and control applications. Figure 1 illustrates an example of installed smart sensors within a bus cabin. As depicted in the figure, indoor air quality sensors are strategically installed at specific locations inside the bus, covering the front, middle, and back sections of the cabin. This arrangement enables real-time monitoring of the cabin's environment. Additionally, based on the sensors' measurements the software platform can notify the driver of any actions required to improve in-cabin conditions.

Figure 1: Example of a smart sensors installation in a bus cabin

Numerical models, on the other hand, involve the use of predictive AI models to estimate IVAQ and temperature, as well as 3D computational fluid dynamics (CFD) models for detailed spatio-temporal analysis of various parameters inside the cabin [73][74][75]. Each of these two numerical approaches has its own advantages and disadvantages and can be used for different purposes [76][77]. For example, AI predictive models are suitable for real-time applications due to their very fast simulation times; however, they tend to produce average estimation data that may have a high level of uncertainty. On the other hand, CFD models are more complex and require a significant amount of time to complete a simulation due to the cell-by-cell methodological approach used, but they provide high-granularity results that allow for a detailed investigation of the distribution of pollutants or airflow inside the vehicle's cabin.

An example of CFD model results for analysing the temperature distribution and flow dynamics inside a bus cabin are presented in Figure 2 a) and b) respectively. As it can be observed from the figure, CFD allows the detail analysis of any parameter of interest at all the locations of the cabin and therefore provides information of local hot-spots or areas of contamination that may affect negatively the IVAQ and the comfort of the occupants. Moreover, CFD results can be used for analysing the effects that mechanical systems, such as the air conditioning, have on the in-cabin environment.

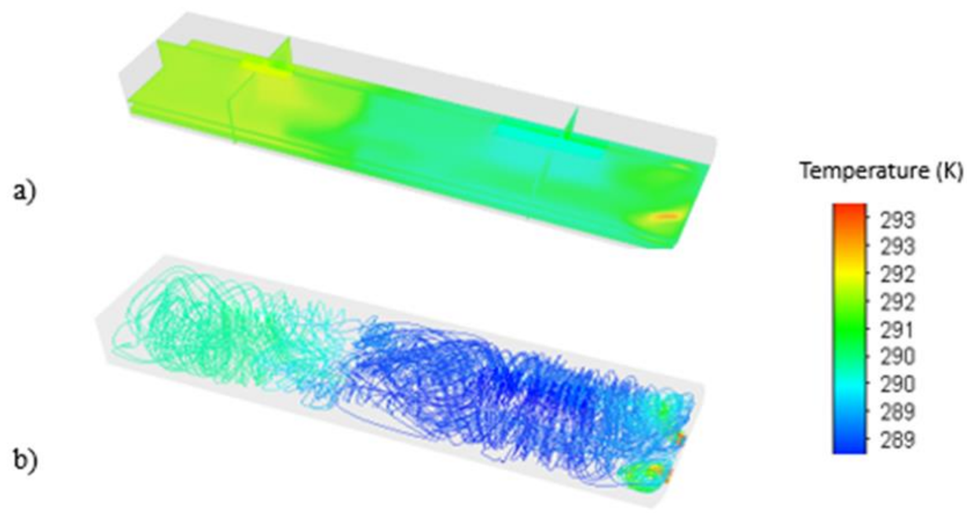

Figure 2: Example of IVAQ CFD simulation of a simplified bus cabin: a) temperature distribution inside the cabin using different planes, and b) air- flow lines colored with temperature.

Both modeling approaches can run standalone test case scenarios or be integrated with the software platform to use live measurements as boundary conditions. This integration allows for the investigation of the effects of air velocity, ventilation systems, window openings, and the number of passengers on both IVAQ and thermal comfort. An IVAQ ranking can be developed by combining both live measurements and simulation data [78].

The overall concept, including the various phases involved in reporting, monitoring, simulating, analyzing, and visualizing IVAQ and thermal comfort conditions, is illustrated in Figure 3. As shown in Figure 3, the software platform not only collects information about the initial conditions of the bus, real-time data from sensors, and numerical results from the models but also facilitates the transfer of information to different tools for triggering simulations or providing updates. This interconnection between the different phases enables the user not only to analyze the data but also to detect potential issues and take action to prevent poor IVAQ conditions, thereby minimizing the risk of passenger discomfort and exposure to pollutants.

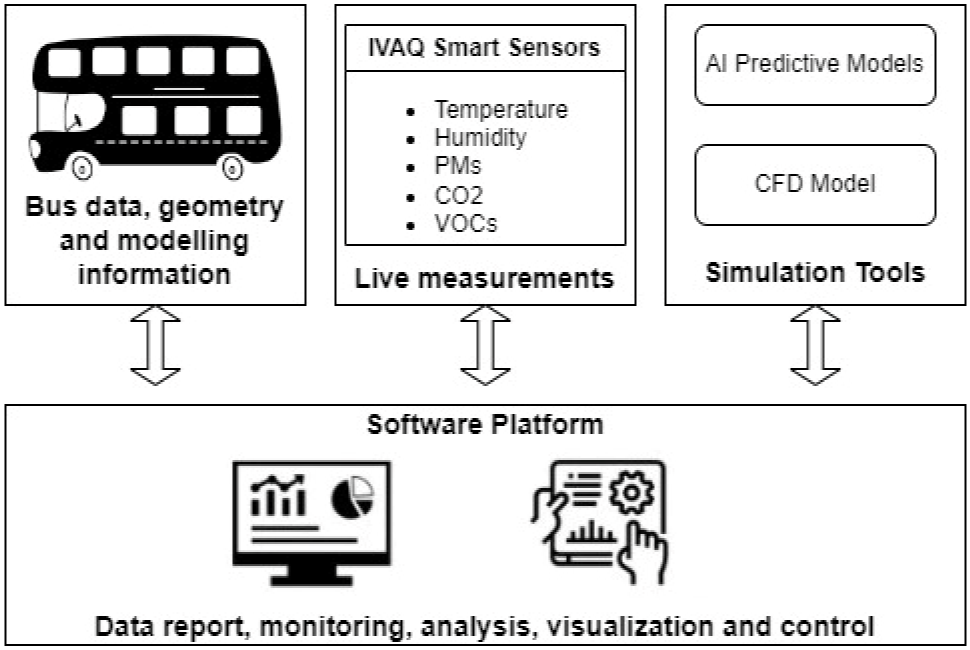

Figure 3:General concept, including the different phases used for reporting, monitoring, simulating, analyzing, and visualizing IVAQ and thermal comfort conditions.

2.1.6. Abnormal Sound Event Detection

This section highlights the state-of-the-art regarding data analysis from acoustic sensors. In sound analysis, it is essential to analyse the signal either in its raw form (waveform in the time domain) or convert it to the frequency domain to extract audio features (e.g., Mel-frequency cepstral coefficients, spectral roll-off, spectrograms, etc.). The advantage of converting to the frequency domain is that it significantly reduces the dimensionality and complexity of the dataset, although some information may be lost in the process.

In our daily lives, we are continuously immersed in a variety of sounds, and the human brain typically identifies these sounds based on prior experience. Artificial Neural Networks (ANNs), inspired by the human brain, can be trained to recognize sounds in a similar way to biological neurons. Recently, substantial progress has been made in this field, particularly in speech-to-text conversion, with major tech companies like Google, Amazon, and Microsoft, spearheading the development of voice-controlled virtual assistants. This technology shows great promise, as voice commands can be significantly more efficient than keyboard input and offer strong market potential [85].

ANNs that process audio signals have garnered substantial research interest in the past decade, demonstrating potential in speech recognition and environmental sound classification. For example, Lane et al. [86] developed a mobile application capable of highly accurate speaker diarization and emotion recognition using deep learning. Piczak [87] tested a simple Convolutional Neural Network (CNN) architecture with environmental audio data and achieved accuracies comparable to state-of-the-art classifiers. Cakir et al. [88] employed one-dimensional (time-domain) Deep Neural Networks (DNNs) for polyphonic sound event detection across 61 classes, achieving an accuracy of 63.8%, a 19% improvement over the hybrid Hidden Markov Model/Non-negative Matrix Factorization method. Recently, Wilkinson et al. [89] applied unsupervised separation of environmental noise sources by adding artificial Gaussian noise to pre-labelled signals, using autoencoders for clustering. However, because background noise in environmental signals is typically non-Gaussian, this method is limited to specific datasets.

In the realm of audio sensor-based surveillance, extensive research has been conducted to reliably identify the audio scene where an event occurs. Audio sensors, such as microphones, offer several advantages:

- Microphones are inexpensive compared to cameras and can be easily deployed in various environments.
- They provide omnidirectional coverage.
- Specular reflections of the audio signal can serve as additional input [90].

However, the main challenge in this field is the unstructured nature of environmental sounds. The signal-to-noise ratio (SNR) for environmental sounds is typically low, especially when the microphone is far from the sound source. Also, unlike speech signals, environmental sounds cannot be classified using phoneme-based approaches, due to their unstructured nature. Other challenges include identifying overlapping events [91], using weakly labelled data for event recognition [92], and the lack of public datasets containing information from multiple sensors [93]. Tsiktsiris et al. [94] extracted the features of the input sound in the frequency domain and used a two-dimensional CNN with an Adam optimizer and ReLU activation function between the convolutional layers, to study the ability of CNNs to generalize under different SNR conditions using the MIVIA audio dataset [95].

2.2. Personalised adaptation

Personalized adaptations in AVs are designed to improve user comfort, convenience, and overall experience by utilizing data about the user's preferences, environment, and health status [79][81]. These systems rely on a combination of sensor networks, artificial intelligence, and IoT technologies to offer real-time, context-aware adjustments that enhance the in-car experience [83][82][80]. Personalized features can be particularly beneficial in various cases:

- easy boarding and off-boarding solutions; adjustable step heights, guided by sensors, can accommodate passengers with reduced mobility, thereby promoting accessibility.
- in-car health and wellness features for the drivers and the rest passengers; such systems can adjust climate control, seating posture, or even issue alerts if the system detects driver drowsiness or stress.
- adjustable lighting and ambiance; adaptive lighting systems provide comfort by adjusting brightness, colour temperature, and ambiance based on time of day, weather conditions, or passenger preferences.
- adaptive climate control; advanced climate control systems rely on user-specific preferences as well as environmental conditions. Utilizing machine learning algorithms, these systems predict and adjust the vehicle's temperature, airflow, and ventilation settings to maintain optimal comfort.
- safe boarding and off-boarding; in the context of accessibility, ensuring that passengers enter and exit the vehicle safely is crucial, particularly for individuals with disabilities or mobility challenges. Automated features, such as sidestep deployment and sensor-based hazard detection near the boarding area, ensure that entry points are in secure, safe locations, reducing the risk of accidents.
- adaptive interior environment; leveraging advances in Artificial Intelligence (AI) and user recognition technologies, vehicles can dynamically adjust various interior settings such as seat position, temperature, lighting, and even entertainment preferences.

Advanced vehicle technologies can simplify the boarding and off-boarding process, like keyless entry, automatic door opening, and adjustable step heights, as well as providing clear instructions and guidance to passengers, indicating the designated entry and exit points, and ensuring that they are in safe locations. Moreover, by recognizing individual passengers and their number, vehicles can automatically adjust seat positions, climate parameters (temperature, airflow, ventilation), internal lighting (brightness, colour temperature, ambiance) music preferences, and other parameters, catering to each user's specific needs and preferences.

2.3. Virtual Assistant Systems

2.3.1. HMIs with intelligent skills and XAI content

The integration of Virtual Assistant Systems (VAS) into Human-Machine Interfaces (HMIs) is advancing rapidly, with intelligent skills and Explainable AI (xAI) content enhancing user interaction, accessibility, and inclusivity. The state-of-the-art in this field focuses on multimodal interaction techniques [96], allowing users to engage with systems through both verbal and non-verbal cues [97]. This makes technology more intuitive and responsive, especially for older adults and people with disabilities who require personalized assistance. The study from Bokolo et al. [98] proposed a design that integrates ML, natural language processing (NLP), and human-computer interaction (HCI) to build the intelligent voice assistants and help elderly people be more mobile and safer. The machine learning models will analyze various data sources (e.g., road condition, weather, and personal goal of mobility) and give the user a personalized safe routing plan and potential danger warning (e.g., fall or accident). NLP has to be used for speech recognition and natural communication through voice commands with Google's Android SDK. There will be a user-friendly graphical interface specially designed for old adults, with strong focus on accessible and easy-to-use user interface design. The interface will be running on smartphone platforms, using open-streaming navigation platforms and building up the application for both android and iOS operating systems. We will also use cloud-based databases for annotation and real-time updates of crowdsourced data.

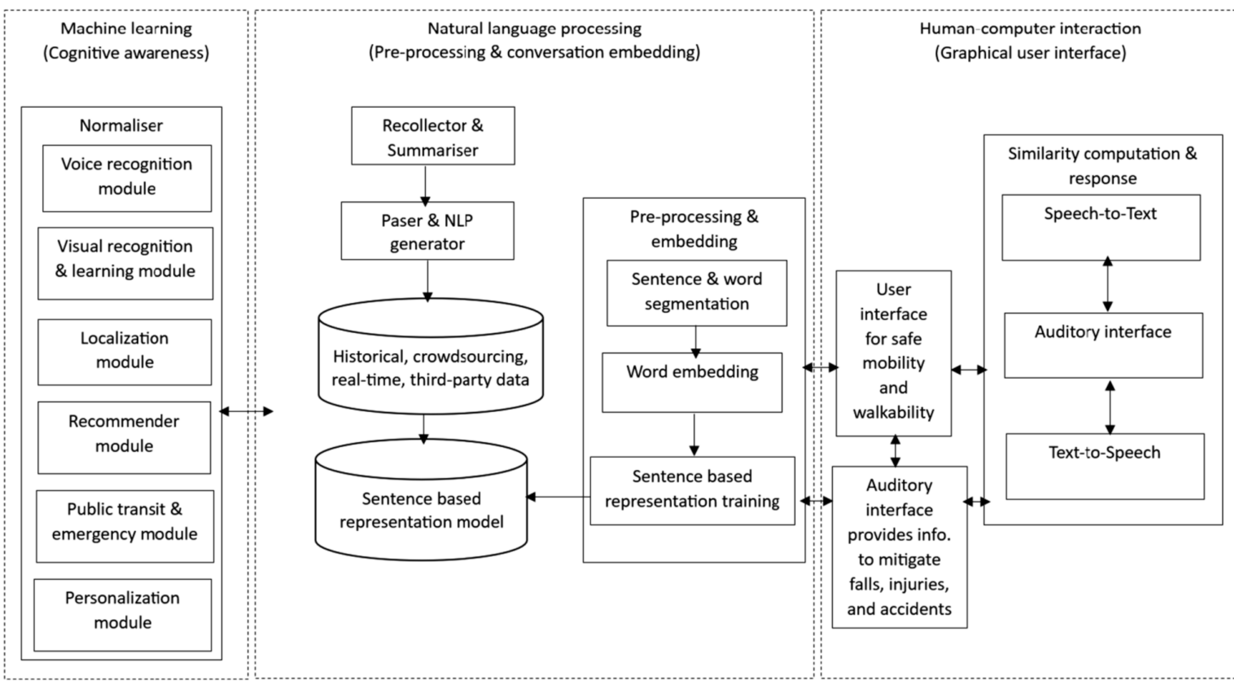

Figure 4: User-centered AI-based Voice Assistant architecture

VAS within HMIs are increasingly inclusive [99], adaptable, and explainable, using multimodal interactions, intelligent skills, and xAI content to meet diverse user needs. Personalization and natural interaction methods are crucial in creating more user-friendly technologies [100], which is shaping the future of human-machine collaboration.

Figure 5: AI drives a suite of new in-vehicle assistants [101]

These systems support multimodal interaction by combining speech recognition for verbal commands with non-verbal cues such as facial expressions, gestures [102],posture, and tone of voice, like:

- Speech recognition for verbal commands [103].
- Facial recognition and gesture tracking to detect non-verbal communication [104].
- Natural Language Processing (NLP) for intelligent dialogue enactment [105].

This enables real-time understanding and response to users' emotions, preferences, and needs. Major companies like Google, Amazon, and Apple are at the forefront of deploying virtual assistants with enhanced multimodal capabilities. Recent surveys provide a thorough overview of the methods and challenges involved in multimodal human-computer interaction, focusing on systems that combine multiple input modalities, such as gestures, speech, and eye movements [106]. Modern VAS also prioritize natural interactions, such as gestures, eye contact, and emotional recognition, which provide intuitive ways for users to communicate. This is especially valuable for individuals with limited motor skills or cognitive abilities. Gesture-based systems, sign language recognition, and eye-tracking are all innovative methods offering accessible and efficient communication alternatives.

Personalization is key to providing seamless experiences for users, particularly those with cognitive or physical impairments [107]. VAS can learn user habits and preferences, offering personalized recommendations, speech adjustments, and proactive assistance tailored to individual needs [108]. This ensures that technology remains accessible and user-friendly, even for individuals with conditions such as early dementia or reduced mobility. This paper focuses on user modelling for adaptive interfaces, emphasizing how HMI systems can learn and adapt based on user behaviour, preferences, and cognitive abilities [109]. Augmented reality (AR) applications in human-computer interaction, focus on how AR can enhance virtual assistant systems and provide explainable, context-aware feedback [110].

Figure 6: Prediction and guidance information received from the vehicle digital twin on the cloud is visualized through an augmented reality (AR) head-up display (HUD), which may include driving proficiency score and its trend, potential action (e.g., hard braking or lane change) and its possibility, as well the driving mood score[1]

xAI plays a critical role in building trust and transparency in VAS, allowing users to understand the reasoning behind system decisions [111]. In high-stakes environments like the automotive sector, xAI provides clear explanations of AI-generated recommendations, ensuring users can trust the system's decisions [112]. DARPA's xAI initiative is explained in detail, providing examples of best practices for implementing explainable AI in various domains, including automotive systems and virtual assistants [113].

1 Wang, Ziran, Liu, Yongkang and Hansen, John H. L.. "7 Enhancing Driver Visual Guidance Through Mobility Digital Twin". Towards Human-Vehicle Harmonization, edited by Huseyin Abut, Gerhard Schmidt, Kazuya Takeda, Jacob Lambert and John H.L. Hansen, Berlin, Boston: De Gruyter, 2023, pp. 95-104. https://doi.org/10.1515/9783110981223-007

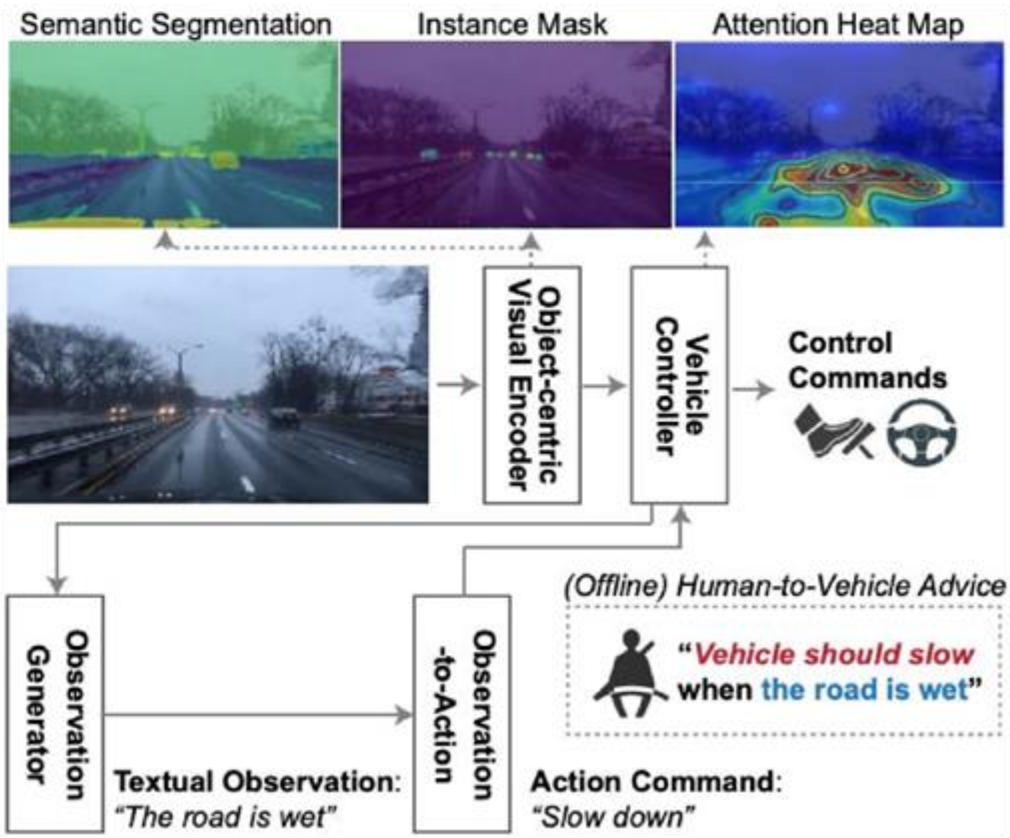

Figure 7: Human advice to the car for relevant action [114]

Supporting older adults and people with disabilities is a growing priority for VAS. By incorporating adaptive features that address physical and cognitive limitations, these systems enable users to maintain independence and improve their quality of life [115]. Assistive devices now incorporate technologies like voice recognition, eye-tracking, and gesture-based controls to offer tailored assistance.

A significant amount of research has been conducted in this field, highlighting the importance of integrating VAS into HMIs. The ongoing research underscores the growing role of VAS in creating more user-centered, intelligent, and transparent technologies. This research focuses on making virtual assistant systems more accessible to older adults by addressing cognitive and physical limitations, emphasizing inclusivity in human-machine interaction [116]. This survey explores how intelligent virtual assistants are being designed to meet the accessibility needs of older adults, particularly in overcoming cognitive and physical limitations [117]. This article addresses the development of virtual assistant systems aimed at compensating for physical and cognitive impairments and promoting inclusiveness [118]. This article reviews assistive technologies and intelligent systems that support people with disabilities, particularly focusing on virtual assistants and adaptive interfaces that enhance inclusivity [119].

2.3.2. HMI evaluation

HMI design in AVs requires meeting a multitude of objective and subjective criteria to ensure both functionality and user satisfaction. These criteria include operational principles, system mode indication, display installation, information presentation, legibility, understandability, and the use of appropriate colour coding, auditory, and vibrotactile warning messages. The primary goal of HMI design is to establish a seamless and intuitive interaction between the driver and the vehicle's systems, thereby enhancing safety, usability, and the overall driving experience messages [84]. To achieve these critical goals, the design and development of HMIs must follow specific development frameworks, design guidelines [120] and established standards [121], (such as **ISO 34503** on test scenarios for automated driving systems). These guidelines ensure that HMI systems meet usability, safety, and accessibility benchmarks and undergo rigorous evaluation procedures to assess their impact on driver behaviour and cognitive load. Standards are also essential to ensure cross-compatibility between different systems and consistency in user experience across various vehicle manufacturers.

Key Evaluation Areas

HMI evaluation involves a detailed examination of multiple factors, with a focus on how the interface impacts driver behavior and attention. Driver distraction and cognitive load are key concerns, as overly complex or poorly designed HMIs can increase mental effort, thereby diverting the driver's attention away from the road. Indeed, ergonomics plays a significant role in HMI design, as display position and button placement must accommodate the driver's natural body movements [122], ensuring that the driver can access essential controls without excessive physical exertion. Voice control systems represent a growing area of innovation in HMI design, as they offer an alternative to traditional visual-manual interfaces. These systems are considered less distracting because they allow the driver to maintain visual focus on the road, even though they can still impose a cognitive workload, particularly when the system's voice recognition performance is suboptimal [123]. Despite these challenges, voice-activated controls are advancing rapidly, with AI-powered systems offering more seamless interactions and better contextual understanding. To optimize the design of HMIs, researchers evaluate gaze paths, glance times, and glance durations using advanced eye-tracking technologies. These measurements provide insights into how effectively the HMI is communicating critical information, such as the vehicle's active automation mode [124]. If a driver must spend too long looking at a display to understand the current state of the vehicle, it can negatively impact their situational awareness, leading to increased reaction times and potentially hazardous situations.

2.3.3. Intelligent Personal Virtual Assistants

2.3.3.1. Next Generation of Virtual Personal Assistants (Microsoft Cortana, Apple Siri, Amazon Alexa and Google Home)

The system comprises of various models that are integrated and intended for real time use and data processing. The Knowledge Base is also separated as online and local consisting of data for created models and users such as gesture, automatic speech recognition (ASR), etc. The Graph Model identifies video and image data in real-time by capturing frames for further data processing in the cloud. Likewise, the Gesture Model is used to record and interpret the movements of the human body and the facial features. The developed ASR model transcribes spoken language into text for further analysis. The Interaction Model helps to co-ordinate the input data and system models and therefore helps in decision making. The Inference Engine feeds with the interaction model to assess conditions and determine implications. The User Model preserves information about a user, such as personal details and past exchange, to customize replies. The Input Model deals with the incoming data from the input devices such as microphones and cameras and on the other hand the Output Model deals with the result of the calculations through the proper output devices such as the display or the speakers [45].

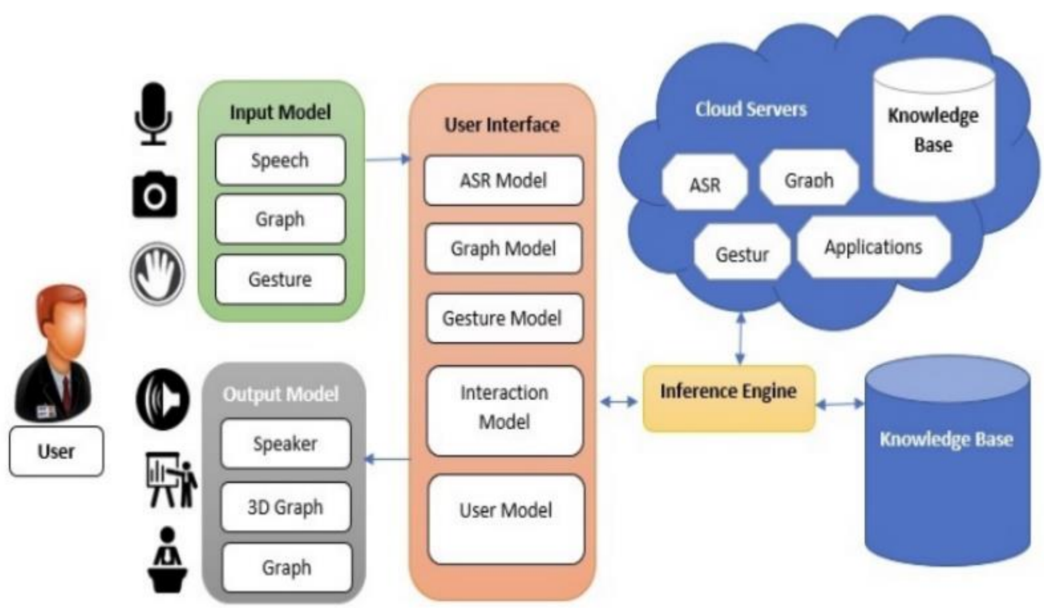

Figure 8: The next generation of Virtual Personal Assistants

2.3.3.2. A Virtual Assistant for Natural Interactions in Museums

The system architecture put forward in this paper comprises a number of components, in order to offer a full-fledged solution. The architecture employs Google Cloud Speech-to-Text (STT) in the process of transcribing the audio recordings into text since this tool is based on machine learning and can easily adjust to the increasing demand. The text is then transferred to the RASA platform[2] that interprets the text with the aid of natural language understanding (NLU), to arrive at the keyword and semantic value. This because the platform was selected owing to its flexibility that allows for rearrangement to accommodate a range of languages. Last of all, to complete the process, SitePal service is used to create avatars that through voice with added lip-sync and facial mimicry service the processed text. For instance, the avatars can be personalized so that they get different models, and different backgrounds as well. The avatars in SitePal were considered to be more attractive as compared to all other alternatives available [46].

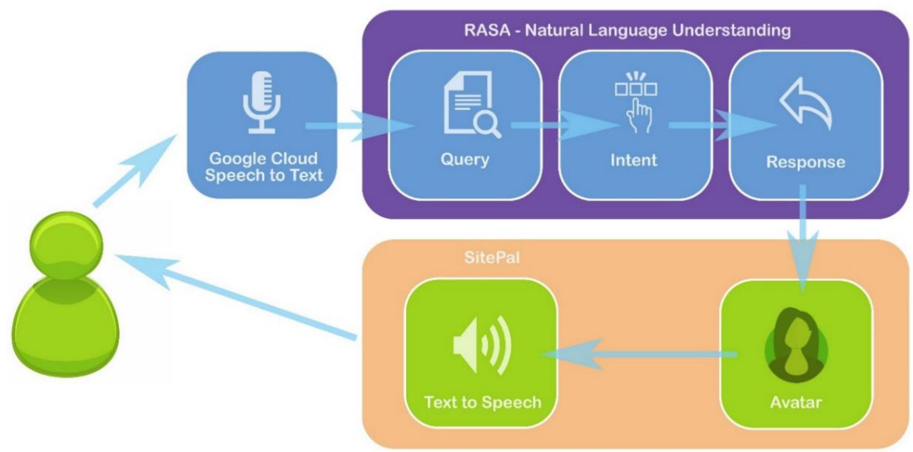

Figure 9: System architecture

2.3.3.3. Voice-based Virtual Assistant with Security

The envisaged virtual assistant (VA) interface architecture has six key components as shown below. About Speech-Text Transcription, the STT converter executes user's voice commands to text using tools that include the google speech API. The last component, Intent and Dialogue Management, deals with the management of the conversation flow and the user's intentions to the actions through rule-based or machine learning algorithms. The Speaker Recognition component deals with voice enrolment, authentication, verification, and identification from libraries such CMUSphinx or Kaldi. The Email Management component handles the user's emails allowing activities such as email creation, reading as well as replying. The Action and API Integra-

[2] https://rasa.com/

tion component communicates with different service APIs for performing some necessary operations. Last is the Text-to-Speech (TTS) wherein the reply from the virtual assistant is translated into speech through the use of TTS tools such as Google TTS API or the Festival TTS [47].

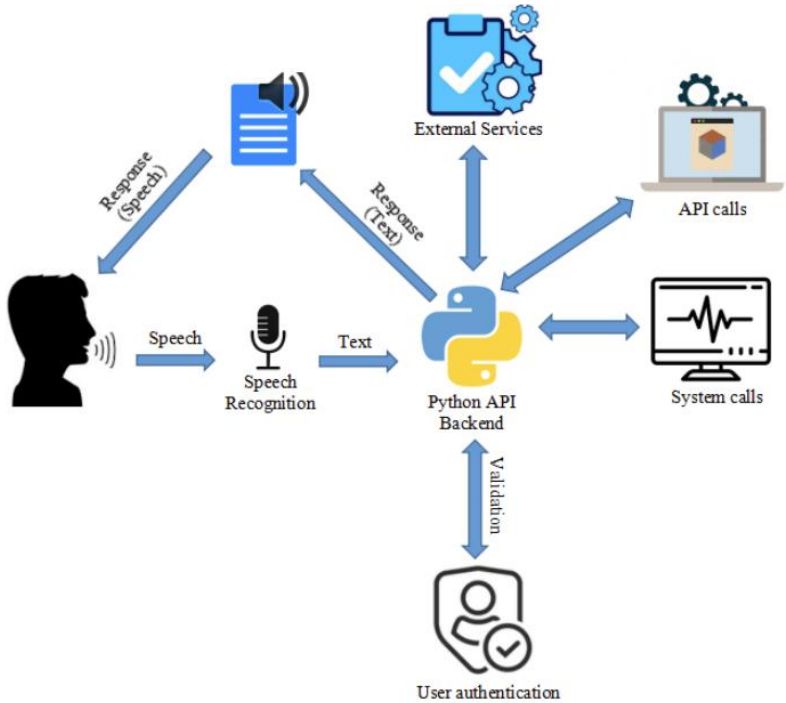

Figure 10: Voice-based Virtual Assistant with security architecture

2.3.3.4. Generative AI-based Virtual Assistant for Reconciliation Research

As stated in the virtual assistant system, the method utilizes the Retrieve-and-Refine technique with the help of Retrieval-Augmented Generation (RAG) that helps in transforming the natural language questions into the SQL queries. First, it queries from an existing embedding index of question-SQL pairs, and such an index can be created with the help of substantially pre-trained models like SentenceTransformers e5-large-v2. The user’s question is translated into an indexing referent of the question, and a vector search engine (e. g. OpenSearch) returns similar questions from the index. The gathered examples are used to create a prompt in the form of a sequence with the corresponding SQL queries and the final SQL query is obtained by using few-shot prompting with an LLM. This prompt also contains specific information of the domain such as the table schema as well as the relevant columns in the table. The SQL query to be executed on the database is post processed with guardrails and error check mechanisms and the retrieved data is displayed to the user [48].

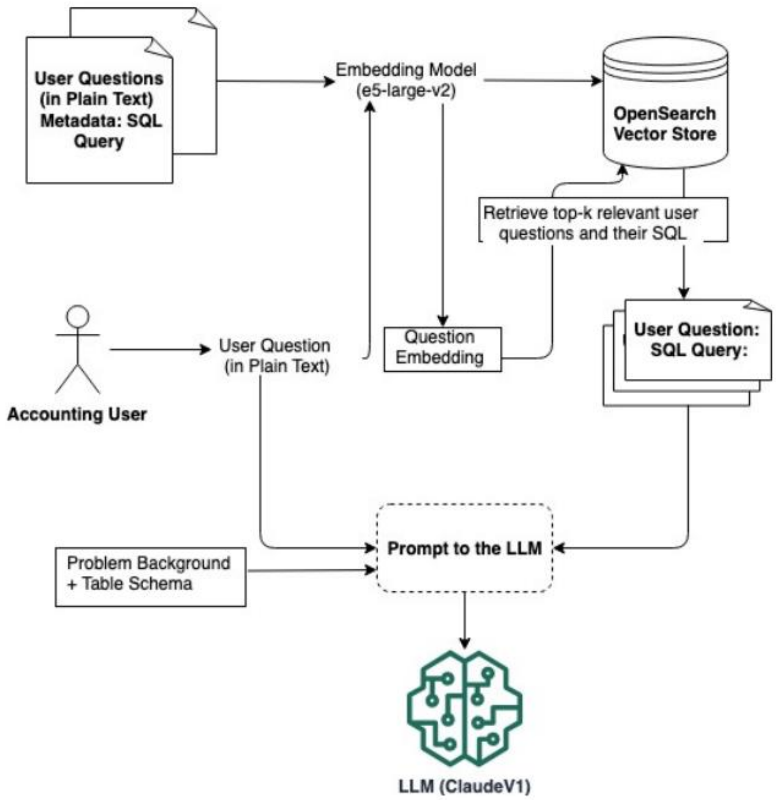

Figure 11: Generative AI-based Virtual Assistant for reconciliation research

2.4. Human factors extraction

The advancement of automotive technologies has driven the development of various tools and techniques to better understand human factors in risk perception, quality of life (QoL), and behavioural change. Extracting human factors for the development of novel solutions in Automated Vehicles (AVs) involves understanding how humans perceive and respond to general risks in AV environments, risks related to their personal data and digital security when interacting with AV systems, and understanding how AVs can enhance users' physical, emotional, social, and psychological well-being.

2.4.1. Risks perception

In general, human factors in risk perception include cognitive, psychological, and behavioural aspects that influence how people interact with and perceive AVs. Chikaraishi et al. [125] recently released a study emphasising that public acceptance of AVs is significantly influenced by risk perception, especially regarding dread and unfamiliarity, aligning with Slovic's psychometric model [126]. The research offers a detailed breakdown of risk dimensions, including voluntariness, controllability, and severity of consequences, providing a nuanced understanding of public concerns about AVs. A key limitation of the study is its regional focus on Hiroshima, Japan, making it difficult to generalise the findings to other cultural contexts where risk tolerance may vary. Additionally, most participants had little or no real-world experience with AVs, which could skew their perceptions, and the study lacks longitudinal data to observe how these perceptions might change with greater exposure to AV technology. These factors highlight the need for broader, cross-cultural studies and real-world AV interaction to validate the results.

Khan et al. [127] presents a comprehensive study on how perceptions of cyber risks, including cyberattacks, safety risks, connectivity risks, privacy risks, and performance risks, influence public acceptance of Connected and Automated Vehicles (CAVs). Conducted across four Organisation for Economic Co-operation and Development (OECD) countries (US, UK, New Zealand, Australia), the research uses a sample of 2062 adults and applies structural equation modelling to assess the relationship between these risks and CAV adoption. The key finding reveals that while perceived cyberattacks elevate concerns about privacy, performance, and safety risks, they have a marginally neutral effect on the overall intention to use CAVs. Interestingly, connectivity risk had no direct impact on usage intent but influenced it through other risk perceptions, especially privacy and performance concerns. A significant limitation of the study is the reliance on participants' perceptions rather than real-world experiences with CAVs, which may lead to bias based on hypothetical scenarios. Additionally, the online survey format may introduce social desirability bias, and the findings may not capture behaviour in real-world contexts. The paper calls for more research involving diverse stakeholders and real-world simulations to strengthen its conclusions.

Another group of researchers [128] investigated how initial trust and perceived risks—specifically, perceived safety risk (PSR) and perceived privacy risk (PPR)—influence public acceptance of AVs. In particular, the authors extended the Technology Acceptance Model (TAM) by incorporating these variables to better understand user attitudes towards Level 3 AVs. Through a structural equation modelling analysis of 216 survey respondents, the study finds that initial trust is the most critical factor in forming positive attitudes towards AVs, more so than perceived usefulness (PU) and perceived ease of use (PEOU). Initial trust is shaped by PU and PSR, but interestingly, PEOU and PPR did not significantly affect trust. The results suggest that enhancing perceived usefulness and reducing perceived safety risks are key to building trust and, subsequently, increasing AV acceptance. However, the study primarily examined initial trust, which is based on respondents' knowledge of AVs from media (Internet, TV) rather than actual experience with the technology. This could skew the findings, as trust and risk perceptions may shift once users have real-world interactions with AVs. Furthermore, this study was focused on Level 3 AVs, where drivers still maintain some control. Thus, findings might differ for higher levels of automation (Levels 4 and 5) where human intervention is minimal.

From the perspective of how drivers engage with in-vehicle information systems (IVIS), Oviedo-Trespalacios et al. [129] explored risky driving behaviours associated with the use of these systems. Based on interviews with 32 Australian drivers, the study finds that while most users primarily employ IVIS for GPS navigation and music, they lack comprehensive knowledge of other system capabilities. Many participants perceive IVIS as non-essential for safe driving and express concerns over the risks of over-reliance on the system, particularly for navigation. The study identifies those risky behaviours, such as prolonged glances at the screen and manual interaction with the IVIS while driving, are common, which increases the risk of crashes. Using the Theory of Planned Behaviour (TPB) [130], the study highlights that drivers believe IVIS use is generally safe if self-regulated, but such self-regulation is often inconsistent. The major limitations include the small and socioeconomically homogeneous sample, which may not fully represent the broader population, and the qualitative nature of the research, which could introduce bias due to participant recall errors or courtesy bias. Additionally, there is a need for further research to address privacy and security risks associated with IVIS, as well as explore strategies to reduce risky interactions with these systems.

The work of Liu et al. [131] provides a comprehensive literature review on how visual risk perception influences braking control behaviour in human drivers. The study emphasises that over 90% of driving-related information is obtained through visual perception, and visual cues such as spatial distance, speed, and time-to-collision (TTC) are critical in determining when drivers initiate braking. The review discusses traditional risk perception metrics, such as time-to-collision and time headway, and derived metrics, such as modified time-to-collision (MTTC), which incorporates relative acceleration. The paper also highlights the influence of driver characteristics (age, gender, driving experience) and environmental factors (spatial and temporal features) on braking behaviour. Various braking control models—threshold-based, error-nulling, evidence accumulation, and affordance-based models—are analysed for their applicability to both manual and automated driving systems. Understanding these factors, along with driver characteristics such as age and experience, aids in creating user profiles for personalised vehicle systems. However, a major limitation is that many of the studies reviewed rely on controlled simulations, which may not fully reflect real-world driving conditions. Additionally, the paper focuses primarily on visual perception, neglecting the potential role of other sensory inputs like auditory or tactile cues, and while it touches on automated driving systems, it does not fully address the application of these models in fully AVs.

2.4.2. Data privacy and security

With the increasing reliance on sensors, AI, and connectivity, AVs face significant cybersecurity risks, including unauthorised data access, system hacking, and privacy breaches. AVs collect vast amounts of personal and operational data, which must be protected to ensure user trust and compliance with global regulations. Emerging threats, such as cyber-physical attacks targeting perception systems, adversarial machine learning exploits, and vulnerabilities in vehicle-to-everything (V2X) communication, highlight the need for robust privacy and security measures. This in turn impacts the perception of cyber risks and the overall acceptance of AVs related technologies.

Liu et al. [132] used qualitative interviews with 36 experts to examine the critical cyber security and privacy concerns surrounding CAVs. The study identifies six core themes impacting the public acceptance of CAVs: awareness, user and vendor education, safety, responsibility, legislation, and trust. Experts emphasised the need for greater public awareness of cyber risks, along with enhanced education for both users and vendors. Trust and transparency were identified as fundamental to fostering acceptance, while clear legislative frameworks and shared responsibility for privacy breaches are crucial to mitigating risks. The study also highlighted the importance of embedding security and privacy protections into the design phase of CAVs to prevent future vulnerabilities. However, the study relied on expert opinions, which may not fully represent the perspectives of general consumers, and the small, UK-focused sample limits generalisability. Additionally, the qualitative nature of the research makes it difficult to quantify the public's acceptance of CAVs based on these expert insights, suggesting that broader public-focused surveys are necessary for further research.

To counterfeit threats specifically in the AVs perception systems, Ghosh et al. [133] proposed a framework that combines traditional asset-centric threat models like ISO/SAE 21434 with system-theoretic approaches such as STPA-Sec to address security vulnerabilities, particularly those reliant on AI-driven object detection algorithms. By introducing AI robustness and object relevancy into the risk assessment model, the framework enhances the detection and mitigation of cyber-physical threats in real-time operational environments. However, the framework remains theoretical, lacking real-world validation, and focuses primarily on camera-based object classification, limiting its applicability to other sensors like LiDAR. The study provides a novel approach to improving AV security, but further empirical testing is necessary to validate its effectiveness and extend its scope.

Cyber risks, liability, and data concerns were identified as key factors affecting the public's acceptance of AVs across Australia, New Zealand, the UK, and the US by Khan et al.[134]. Based on a survey of 2,062 adults, the study develops measures for liability concerns, data sharing practices, and the willingness to adopt AVs. Key findings reveal that 70% of respondents are concerned about liability arising from cyber risks, and participants with higher concerns about data sharing and security were less likely to adopt AVs. However, those comfortable with data sharing and regular patching (software updates) showed a greater intent to adopt AVs. Additionally, concerns about in-vehicle data collection, such as location tracking and in-car conversations, were significant, with over 70% of participants expressing unease about these issues. The study's findings are limited by its geographical scope, focusing only on four developed countries, which may not fully represent attitudes in other regions, especially developing nations. Furthermore, the research relies on perceptions rather than real-world interactions with AVs, which could lead to different outcomes in actual use cases.

Seetharaman et al. [135] examined the key factors that contribute to cyber threats in AVs and their significance. Using a modified framework that combines the Cyber Cycle and Diamond Model of Intrusion Analysis with the Active Cyber Defense Cycle, the study identifies seven major factors influencing AV cyber threats: socio-cultural factors, regulatory issues, intelligent transportation systems (ITS), predictive measures, cyber-attacks, in-vehicle network vulnerabilities, and trust. Key findings highlight that the workload of driverless systems correlates strongly with cyber-attacks and threats, and in-vehicular network vulnerabilities significantly influence trust in AV technology. Additionally, the study emphasised that privacy and data protection are critical to maintaining public trust in AVs. However, the research is largely conceptual and calls for further empirical validation of its integrated cyber-defence models. The focus is on first-generation AVs, which may not fully apply to more advanced, fully autonomous systems. Future research could expand the scope to consider socio-economic factors and real-world applications in intelligent transportation systems.

2.4.3. Quality of life

QoL encompasses a broad range of factors, including convenience, safety, stress reduction, accessibility, and overall user satisfaction with their interaction with AVs. Garzia et al. [136] investigated how the COVID-19 pandemic influenced public perceptions of safety and risk associated with car and motorcycle travel in two major cities: London and Rome. The study used opinion mining and sentiment analysis of tweets posted between March 23 and July 9, 2020, to understand the emotional components linked to transportation in both cities during different phases of the pandemic. The researchers employed Open-Source Intelligence (OSINT) techniques to gather and process tweets, examining the emotional responses triggered by terms related to transportation. The analysis revealed distinct emotional patterns across different phases, with predominant emotions like fear and sadness during the early lockdown phases, and a gradual shift toward more positive emotions like joy as restrictions eased. The research highlights the effectiveness of using sentiment analysis of social media data to track public perceptions of safety and risk in real time. However, the study's reliance on Twitter data may limit its representativeness, as Twitter users do not necessarily reflect the broader population. Additionally, automated sentiment analysis tools, while useful for processing large data sets, may oversimplify complex emotions, missing out on contextual nuances.

Ping et al. [137] presented a study that uses deep learning techniques to model subjective risk perception in drivers. The research focuses on identifying how drivers perceive risks under different driving conditions, aiming to improve driving safety by predicting when a driver might feel at risk. The study used video recordings of city road driving and a Long Short-Term Memory (LSTM) neural network to analyse the impact of environmental factors, such as road conditions and surrounding vehicles, on driver risk perception. The model was trained using risk assessment data from drivers of varying experience levels and was able to predict subjective risk perception with an accuracy rate of 81.55%. The model helps identify when drivers feel unsafe, contributing to better driver assistance systems that can reduce stress and improve overall driving experiences, thereby enhancing quality of life. However, the study is limited by a controlled environment and small sample size, which may not fully represent diverse real-world conditions. It also focuses mainly on visual cues, missing out on other sensory inputs that could influence risk perception.

On a similar note, Perello-March et al. [138] explored how physiological responses can be used to assess risk perception during highly automated driving (HAD). By monitoring heart rate variability (HRV) and skin conductance responses (SCR) during driving scenarios, the study identifies that HRV is more effective in capturing arousal during slow-evolving, low-to-moderate risk situations, while SCR is more sensitive to sudden, high-risk events. The study highlights the potential for driver state monitoring systems to use these physiological indicators to detect driver readiness for manual takeovers during critical situations in HAD. The study was based on simulated driving conditions, which may not fully replicate real-world scenarios. The small sample size (20 participants) also limits the generalizability of the findings. Further research in real-world environments is needed to validate these physiological measures.

Brell et al [139] examines how public perceptions of risk and benefits related to autonomous and connected driving influence their potential to enhance quality of life. The study finds that while AVs offer benefits such as increased comfort, time-saving, and improved mobility for those unable to drive, these potential quality-of-life improvements are overshadowed by high concerns around data privacy and cybersecurity risks. Despite the advantages AVs may bring in reducing stress and increasing convenience, especially for elderly or disabled users, these concerns remain significant barriers to public acceptance. Importantly, individuals with more experience using ADAS tend to perceive lower risks related to AVs, which could translate to higher QoL through increased trust in the technology. However, even experienced users express concerns over data privacy, suggesting that addressing these issues is crucial for AVs to truly enhance quality of life. The study's limitations include its reliance on perceptions rather than real-world experience and its focus on German participants, which may limit the generalizability of the findings.

Sankeerthana et al [140] explored how the adoption of AVs could improve QoL for road users, particularly through increased safety, reduced driving stress, and improved traffic efficiency. However, public perceptions of risk, especially regarding safety and trust in the technology, remain significant barriers to widespread adoption. The study emphasises that vulnerable road users, such as pedestrians and cyclists, perceive higher risks when interacting with AVs, which could negatively impact their overall sense of safety and well-being. The review highlights that addressing these concerns through technological transparency, such as clear communication between AVs and human road users, could enhance trust and improve the public's willingness to adopt AV technology, ultimately contributing to a higher QoL by reducing accidents and traffic-related stress. The study, however, relies heavily on surveys and simulations, which may not fully capture the real-world effects of AVs on quality of life.

3. User Centered design (UCD) methodology

This section presents the User-Centered Design (UCD) methodology adopted to guide the development and evaluation of Autonomous Vehicle (AV) systems, ensuring that user needs, preferences, and experiences remain at the core of the design process. Rooted in the fields of human-computer interaction (HCI) and cognitive psychology, UCD emphasizes the iterative involvement of users throughout the design stages. This approach ensures that the resulting product is functional, intuitive, inclusive, and aligned with user expectations. The primary objective of the UCD methodology in this project was to identify and address the psychological, social, and physical factors influencing users' interactions with AVs.

To achieve these objectives, we conducted focus group sessions, a key element of the UCD methodology. Focus groups were selected as the primary data collection method due to their ability to capture users' subjective experiences, group dynamics, and shared perspectives. These sessions provided a platform for direct engagement with users, gathering in-depth feedback on multiple aspects of AV usage, such as user trust, safety, accessibility, and emotional comfort.

The evaluation protocol for the focus groups was systematically designed to assess how well AV systems meet user needs and expectations. Our evaluation concentrated on several key factors:

1. **Cognitive Load and Attention**: We investigated how the AV's Human-Machine Interface (HMI) design impacts cognitive load, distraction, and attention. Participants reflected on HMI elements such as display placement, voice control systems, and visual/auditory alerts, highlighting areas where the interface either facilitated or hindered cognitive ease during interactions.
2. **Trust and Safety**: Building trust between users and AV systems was a major focus in these discussions. Participants shared insights into transparency in decision-making, predictability of the vehicle's actions, and the overall sense of safety when using an AV, all of which are crucial factors in fostering user confidence and trust in autonomous technology.
3. **Social and Affective Perspectives**: The social factors and emotions that shape the user experience in AVs were also evaluated. Participants considered how AVs might support or hinder social interactions among passengers and reflected on the emotional responses associated with riding in an AV, including feelings of excitement, anxiety, and discomfort.

4. **Accessibility and Inclusivity**: Inclusivity emerged as a central topic in focus group discussions. Participants with disabilities provided insights on the physical and digital accessibility of AVs, emphasizing the importance of seamless assistive features, such as ramps, lifts, auditory cues, and adaptable digital interfaces for users with visual or cognitive impairments.

This section outlines the methodologies used to analyze the data collected from these focus groups, presenting key findings that highlight user requirements and inform design decisions. The results derived from this evaluation serve as actionable insights, guiding the project team in creating an AV system that aligns with diverse user expectations and requirements.

3.1. Introduction to UCD

UCD is a methodology that poses the final users in the core of the process, analysing and gathering their stated and latent needs under different points of view.

User-Centered Design has its roots in human-computer interaction (HCI) and cognitive psychology, with early contributions from researchers like Norman who emphasized the importance of designing products that fit human cognitive and physical capabilities [143] .He argued that poor design often comes from a lack of understanding of how people interact with objects, leading to products that are difficult to use. The concept of UCD was further explored with the development of frameworks that incorporated user feedback into the design process, as seen in works by Nielsen [144][145]. These frameworks provided the main methodologies for understanding user needs and integrating them into product design.

The core idea behind UCD is to create products, services, or systems that are not only functional but also highly usable, accessible, and meaningful for the people who will use them. By focusing on users throughout the entire design process, UCD aims to ensure that the outcome is closely aligned with their expectations and requirements [141]. The UCD process involved designers to deeply understand the users they are designing for. This involves gathering insights into their behaviours, motivations, and the specific contexts in which they will interact with the product. By thoroughly understanding these factors, designers can identify key user needs and challenges. As addressed in ISO 9241-210 for an ideal UCD process is fundamental the involvement of stakeholders at every stage of the design process. Rather than relying solely on assumptions, designers actively engage with users through methods such as interviews, surveys, focus groups [142]. This ongoing dialogue ensures that the design evolves in a way that remains connected to the experiences and expectations of the stakeholders. This method is especially valuable for complex systems, such as AVs, where user trust, safety, and comfort are critical to the system's success.

By understanding the emotions, frustrations, and desires of the users, it is possible to create solutions that are not only functional but also enjoyable and satisfying to use. Focusing on empathy allows us to create products that truly connect with users, making them feel understood and valued. This deeper connection between the product and its audience leads to a more meaningful and engaging experience.

3.2. User-Centered Design Methodology for User Requirements Analysis

In alignment with the AutoTRUST project's goal of creating accessible, inclusive, and user-friendly autonomous vehicle (AV) systems, the User-Centered Design (UCD) methodology outlined in this deliverable is fundamental to the process of defining user requirements. By prioritizing direct engagement with end users, the UCD approach enables project partners to develop a detailed understanding of user needs, preferences, and expectations, which directly informs the specification and refinement of system requirements.

3.2.1. Applying UCD to User Requirements Collection

To accurately capture user requirements, the UCD methodology leverages structured interactions, such as focus group sessions, to gather qualitative data from diverse user groups. These interactions are carefully designed to explore a range of topics—such as safety, trust, cognitive load, accessibility, and emotional responses to AVs—each of which provides critical insights into how users expect AV systems to perform and what features they find most valuable. This information is translated into concrete user requirements that serve as guidelines for the design and development of AV systems within the project.

- Comprehensive Requirement Identification: By engaging users from various backgrounds and with different levels of experience with AVs, the focus groups help uncover both explicit needs (e.g., the need for accessible design features) and latent needs (e.g., preferences for specific HMI designs). This ensures that the identified requirements cover a broad spectrum of functional, social, and psychological dimensions, which are essential to making AVs user-friendly and inclusive.

- Iterative Requirement Refinement: The UCD process is inherently iterative, allowing user requirements to be revisited and adjusted as new insights emerge throughout the project lifecycle. As such, each phase of user engagement—whether through initial focus groups, pilot studies, or later-stage evaluations—offers an opportunity to refine these requirements based on real user feedback. This approach helps maintain alignment between user expectations and AV system development.
- User-Centric Documentation and Validation: Following data collection, a structured thematic analysis is used to distill the data into actionable user requirements. This analysis transforms qualitative insights into specific, measurable guidelines, making them accessible for project partners. In this way, the UCD methodology aids not only in initial requirements gathering but also in ongoing validation, ensuring that AV design decisions remain responsive to user needs.

3.2.2. Benefits to Project Partners in the User Requirements Process

For project partners, the UCD methodology outlined in this deliverable offers a strategic framework to integrate user requirements seamlessly into each phase of AV development. It provides clear, user-informed insights into areas such as:

- Human-Machine Interface (HMI) Requirements: Specific user feedback on HMI elements such as screen layout, voice activation, and warning signals translates into detailed design specifications, enabling partners to develop intuitive interfaces that minimize cognitive load and enhance ease of use.
- Safety and Trust: Discussions on user perceptions of safety and trustworthiness in AVs produce requirements related to system transparency, predictability, and reliability, informing technical specifications that foster trust and reassure users.
- Accessibility and Inclusivity: Through direct feedback from participants with disabilities, the UCD approach highlights accessibility needs, such as physical assistive features and adaptable digital interfaces, allowing project partners to design AVs that are inclusive and accessible to all.
- Emotional and Social Aspects: Insights into emotional responses and social considerations offer guidelines for improving user comfort and facilitating social interactions, such as integrating features that reduce anxiety or enhance connectivity among passengers.

Therefore, the UCD methodology provides a structured, evidence-based approach to identifying, analyzing, and documenting user requirements, ensuring that AV development within the

AutoTRUST project is grounded in real user insights. This approach equips project partners with a detailed, user-centered framework for building AV systems that meet diverse user needs, thereby supporting the project's overarching mission to advance autonomous mobility solutions that are safe, inclusive, and widely accessible.

4. Focus group

Following the UCD Methodology to ensure a strong focus on user needs and preferences, we decided to use focus groups as a key method for gathering in-depth insights. By engaging different stakeholders directly through focus group discussions, we were able to explore their experiences, expectations, and challenges in a structured manner, which significantly informed the design process. In this subsection we discuss the evaluation protocol, design and structure of the focus groups, along with the process followed during the sessions. It includes information on how participants were selected, how the sessions were structured to elicit meaningful feedback, and the types of questions or discussion points used. This section also covers the logistics of running the focus groups, including any challenges encountered and how they were addressed.

4.1. Evaluation protocol

The purpose of the evaluation phase in the UCD process is to systematically assess how well the design meets user needs and expectations. This section outlines the evaluation protocol employed in the focus group, detailing the methods, participant selection criteria, and the procedures followed to gather relevant data.

The selection of participants was a critical aspect of the evaluation protocol. Participants were chosen to reflect the diversity of the target user group, ensuring that the evaluation results would be relevant and generalizable. The selection criteria included factors such as age, gender, and expertise, to capture a wide range of perspectives. This was important to assess the system's usability across different levels of familiarity. Furthermore, special consideration was given to including participants with specific accessibility requirements, allowing the evaluation to address the inclusivity of the design.

The sessions had a facilitator who guided the conversation using a guide (described in the next section). The discussions were conducted via Microsoft Teams, utilizing PowerPoint Live for presentations, as shown in Figure 12. The sessions were video and audio-recorded and subsequently transcribed for thorough analysis.

During these sessions, participants were encouraged to share their experiences with the AVs writing their thoughts in the PowerPoint Live accessible to everyone. Topics covered during the session are described in the next section.

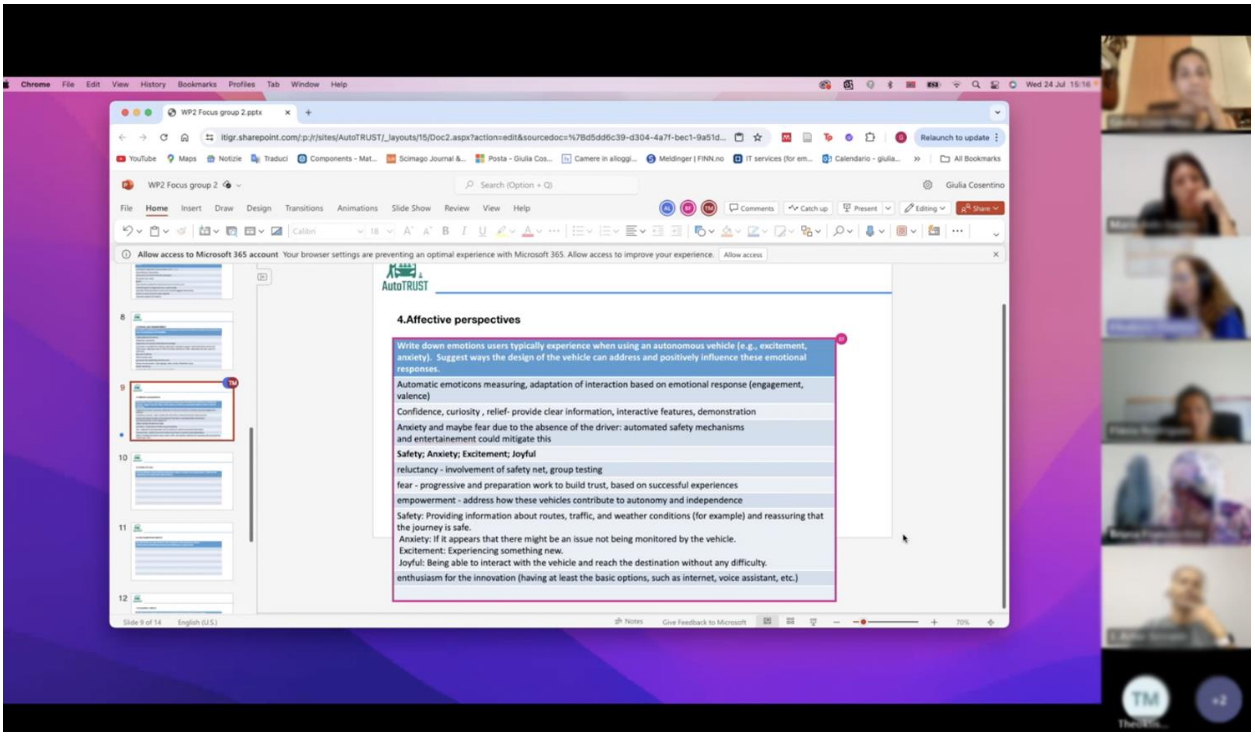

Figure 12: AutoTRUST Focus group via Microsoft Teams

4.2. Participants and focus group structure

In total, 17 participants were involved in the evaluation, divided into 2 groups for the focus group discussions sessions (2 hours each). The participants who were between the ages of 35 and 54, with a fairly equal distribution of male and female respondents. In terms of educational background, the participants represented a range of qualifications, from high school-level education to doctorate degrees, with a notable concentration of professionals holding master's degrees. The respondents came from diverse fields, including engineering, project management, business development, consultancy, and research, reflecting a broad spectrum of expertise and professional experiences. When asked about their familiarity with AVs, most participants indicated they were either somewhat familiar or familiar with this technology. This suggests that while the majority have awareness or understanding of AVs, there may still be varying degrees of knowledge about the specific capabilities or implications of the technology. A significant portion of the participants had firsthand experience with AVs, having used or ridden in them. Many of these experiences involved self-driving cars such as those produced by Tesla or Waymo, or autonomous shuttles. Others had experience with vehicles equipped with advanced driver-assistance systems (ADAS), which offer semi-autonomous features. However, not all respondents (four of them) had used or ridden AVs. Overall, the participants are familiar with AVs and have varying levels of direct experience with them. To ensure inclusivity and gather diverse perspectives, a blind passenger participated in the focus group discussions. Their unique insights provided valuable input on the accessibility and usability of the proposed technologies for individuals with visual impairments. The diverse participant pool ensured that the evaluation captured a broad spectrum of user experiences and needs.

The focus group was structured as follows:

- **Introduction (5 minutes):** The session began with a warm welcome, an explanation of the focus group's purpose, and a brief overview of confidentiality guidelines.
- **Icebreaker (10 minutes):** Participants introduced themselves and shared their experiences related to AVs and digital inclusion, helping to create a comfortable and engaging atmosphere.
- **Main Discussion (100 minutes):** For each discussion topic (7 in total), participants spent 5 minutes writing down their thoughts, followed by a 10-minute moderated discussion led by the facilitator. This structure ensured that all voices were heard, and that the discussion remained focused and productive.
- **Conclusion and final thoughts (5 min):** In the concluding part of the session, participants were given the opportunity to share any additional insights or recommendations they might have.

During the focus group session, participants engaged in a series of topics designed to explore various aspects of AV use from multiple perspectives. The discussion was structured around key themes, each addressing different dimensions of user experience and design considerations. These themes were carefully selected to capture the full range of factors that influence how users interact with and perceive AVs. The following topics were covered during the session:

Psychological Perspectives:

Participants were asked to reflect on the psychological factors that influence comfort or discomfort when using an AV. They were prompted to identify at least three crucial psychological factors, such as trust in the vehicle's technology, the sense of control, and the anxiety associated with unexpected situations. The discussion then explored how specific features or design elements could enhance these factors or mitigate discomfort during a ride in an AV.

Diverse User Representation:

The group examined the importance of inclusivity in AV design. Participants were encouraged to list essential accessibility features and ethical considerations necessary to ensure that AVs cater to all users, including those with disabilities. The discussion focused on identifying the features that would make AVs more accessible and the ethical implications of design choices.

Social Perspectives:

The discussion turned to the social aspects of traveling in an AV. Participants were asked to think about how AVs could facilitate social interactions among passengers. They were also invited to suggest features that could help users feel more connected or engaged, whether with fellow passengers or with other drivers on the road.

Affective Perspectives:

Participants were prompted to consider the range of emotions users typically experience when using an AV, such as excitement or anxiety. The discussion then explored how the design of the vehicle could be tailored to address these emotional responses positively, creating a more comfortable and enjoyable experience for users.

Context of Use:

The participants explored how different contexts—such private vs. public transportation—might influence the requirements for AV features. Participants were asked to list the specific ways in which these varying contexts could shape the design and functionality of the vehicle.

User Experience Factors:

Participants were invited to identify the most critical factors influencing users' experiences with AVs, such as safety, ease of use, and comfort. The discussion also focused on how these factors should be prioritized when defining user requirements, ensuring that the design aligns with what users' value most.

Evaluation Criteria:

The group discussed the key aspects and areas that need to be considered during the pilot studies' evaluation of AVs. Participants were asked to think about what criteria would be most important to assess the success of the pilot studies, ensuring a comprehensive evaluation of the vehicle's performance.

4.3. Data analysis

We conducted a thematic analysis aimed at identifying key themes that emerged from the discussions and merging insights from both focus group sessions. Below the steps taken during the analysis:

Step 1: Familiarization with the data

The first step in the thematic analysis involved familiarizing with the content of both the transcription and the shared PowerPoint. This included carefully reading through the transcripts and notes from the focus group discussions. The goal at this stage was to gain a deep understanding of the participants' experiences, concerns, and insights related to AVs.

Step 2: Initial coding

Following the familiarization process, we began the initial coding of the data. This involved identifying significant statements, phrases, and ideas that appeared to be important or recurrent across the discussions. Codes were assigned to segments of text that related to specific topics, such as trust in technology, safety concerns, social interaction, accessibility, and user experience. These codes served as the foundation for identifying broader themes.

Step 3: Identifying themes

After coding the data, we reviewed the codes to identify potential themes. Themes are broader patterns that capture something significant about the data in relation to our aim. In this analysis, several key themes were identified based on the topics discussed.

Step 4: Merging insights from both sessions

Once the initial themes were identified, we proceeded to merge insights from the two focus groups. Both focus group discussions had their unique insights, but they also shared common concerns and themes. For example, both discussions highlighted the importance of trust in technology and safety concerns as critical factors. By comparing the themes from each discussion, we were able to create a unified set of themes that included both discussions.

Step 5: Refining themes and sub-themes

In this step, we refined the identified themes and organized them into main themes and sub-themes. For instance, under the theme of Psychological Perspectives, sub-themes such as Trust in Technology and Safety and Security were developed. This process involved grouping related codes and ensuring that each theme was distinct and coherent.

Step 6: Reviewing and finalizing themes

The next step was to review the themes to ensure that they accurately reflected the data. We revisited the original transcripts and notes to verify that the themes were well-supported by the data. This step was crucial to ensuring the reliability and validity of the analysis.

Step 7: Writing the guidelines based on the thematic analysis

The final step involved defining guidelines based on the thematic analysis. This included detailing each theme, providing explanations, and integrating relevant quotes from the discussions to support the findings. The analysis was structured to reflect the most significant insights gained from the focus groups, providing a comprehensive understanding of the participants' views on AVs.

5. Results

This analysis presents the key themes and sub-themes that emerged from the focus group discussions. Each theme reflects critical aspects of user experiences, expectations, and concerns regarding AVs. The insights are supported by direct quotes from participants to illustrate the depth of the feedback collected.

5.1. Psychological Perspectives

Trust in Technology

Participants repeatedly emphasized the need to trust the technology behind AVs. Trust was identified as a foundational element that influences overall comfort and willingness to use these vehicles. Several participants expressed concerns about the transparency of decision-making processes within the vehicle's systems. They wanted assurance that the vehicle would make safe and reliable decisions, especially in complex or unexpected situations.

- **Quote:** "I want to know why an AV makes a specific decision. It’s about predictability and transparency."

Safety and Security

Safety emerged as a top concern, with participants discussing both physical safety and the sense of security while using an AV. The need for clear communication from the vehicle about its actions was frequently mentioned to alleviate anxiety. They discussed anxiety about unexpected situations, such as traffic jams or route changes, and highlighted the importance of the AV providing continuous updates about the journey. The ability to predict and explain the vehicle's actions was seen as crucial for user comfort.

- **Quote:** "Feeling safe and secure in an AV is my top priority."

Ethical Concerns

Participants also raised ethical concerns, particularly related to privacy, data security and the moral decisions that AVs might have to make. There was a strong desire for ethical considerations to be embedded within the technology, ensuring that decisions made by the vehicle align with societal norms and individual values.

- **Quote:** "Trust in technology is crucial. I need to know that the vehicle is taking care of my safety."

Explainability

Meaningful transparency strategies are needed to inform road users and pedestrians of data collection in a CAV operating area. Individuals and the public need to be adequately informed and equipped with the necessary tools to exercise their rights.

- **Quote:** “I want to know why an AV makes a specific decision” or “See with the eyes of the vehicle”

5.2. Social Perspectives

Facilitating Interaction

Participants discussed the potential for AVs to facilitate social interactions among passengers. Some suggested that the vehicle could be designed to encourage conversation through seating arrangements or interactive features. However, there was also a recognition that not all users would want to engage socially during their ride.

- **Quote:** "Seats facing each other could support interaction, but I still value my privacy."

Need for Privacy and Personal Space

While social interaction was seen as a potential benefit, participants also highlighted the importance of maintaining privacy and personal space. Participants mentioned not wanting to overhear other passengers' phone conversations and the importance of being able to find a free seat without assistance. The ability to choose whether to engage with others was considered essential for a positive user experience.

- **Quote:** "I’m not sure I want to interact with other passengers. If I do, I’ll just talk to them."

5.3. Diverse User Representation

Physical Accessibility

Ensuring physical accessibility for all users, including those with disabilities, was a major theme. Participants emphasized the need for features such as ramps or lifts for wheelchair users and adequate space for assistive devices, as well as sound cues for blind passengers. The discussion also touched on the importance of designing these features to be seamlessly integrated into the vehicle.

- **Quote:** "Ramps or lifts are essential to facilitate easy onboarding and offboarding for wheelchair users and those with mobility impairments."

Digital Accessibility

Participants also stressed the importance of digital accessibility, particularly the need for an app that is fully accessible to users with various disabilities, including real-time updates. This included considerations for visual, auditory, and cognitive impairments, ensuring that all users can access information and control the vehicle as needed. There was a strong desire for these digital solutions to be integrated from the start, rather than added as an afterthought.

- **Quote:** "Digital accessibility is often overlooked. We need apps that are usable by everyone, including those with disabilities."

5.4. Affective Perspectives

Initial Excitement vs. Routine Use

Participants noted that while there is initial excitement about using AVs, this feeling tends to diminish over time as the experience becomes routine. Some mentioned that they would eventually just focus on their phones or other activities during the ride, indicating a shift towards feeling safe and comfortable. This shift from excitement to a more subdued emotional state highlights the importance of designing for long-term user satisfaction, not just the initial novelty.

- **Quote:** "The first time in an AV, I was excited. But after a while, it just felt normal, maybe even safe."

Discomfort and Motion Sickness

The physical comfort of users was another key concern, particularly regarding motion sickness. Participants discussed how the unfamiliar driving patterns of AVs could enhance the discomfort, suggesting the need for ergonomic design and motion sickness prevention features.

- **Quote:** "Discomfort due to unfamiliar driving patterns of an AV was a significant issue. It didn’t feel like a human was driving."

5.5. Context of Use

Public vs. Private Transportation

The context in which AVs are used significantly influences user requirements. Participants highlighted different needs for public versus private transportation, with public transportation requiring more flexible seating and real-time updates, while private transportation prioritized personalization options like climate control and entertainment.

- **Quote:** "The number of users certainly influences the features of the vehicle. Public transportation needs flexible seating, while private transportation requires personalization."

Fixed Schedule vs. On-Demand Services Participants also discussed the different expectations for fixed schedule services compared to on-demand services. Punctuality was emphasized for fixed schedules, while clear communication about waiting times and route options was seen as crucial for on-demand services.

- **Quote:** "For fixed schedule services, I want the vehicle to be on time. For on-demand services, knowing the waiting time and connection options is crucial."

5.6. User Experience Factors

Prioritizing Safety and Accessibility

Safety and accessibility were consistently highlighted as the most critical factors influencing user experience. Participants emphasized that these elements should be the top priority when designing and evaluating AVs.

- **Quote:** "Safety is the most critical factor for me. Without it, nothing else matters."

Comfort Considerations

Comfort, while important, was considered secondary to safety and reliability. However, participants still highlighted the need for comfortable seating, climate control, and a smooth ride to enhance the overall experience.

- **Quote:** "Comfort is important, but for short trips, safety and reliability take precedence."

Inclusive design/ inclusive language

CAV should also be designed in a way that takes proactive measures for promoting inclusivity, neither discriminating against individuals or groups of users, nor creating or reinforcing large-scale social inequalities among users.

5.7. Evaluation Criteria

User Acceptance and Simplicity

Participants suggested that the evaluation of Avs should focus on user acceptance, simplicity, and ease of use. The criteria should consider how intuitive the system is and how easily users can interact with it.

- **Quote:** "Acceptance and simplicity should be key criteria in evaluating the service. How easy is it for people to use?"

Inclusivity and Privacy

The evaluation should also account for inclusivity, ensuring that the system is accessible to all users, including those with disabilities. Privacy concerns were also highlighted, emphasizing the need for secure data handling and user control over personal information.

- **Quote:** "We should measure the number of people with disabilities using the service. It's important to ensure inclusivity."

Gender balance

It is essential that diversity is built into all aspects of the design models of CAV systems and services. Such diversity should include gender, ethnicity and other socially pertinent dimensions.

6. User Requirements and guidelines

6.1. Introduction

Informed by the thematic analysis of focus group discussions, this section presents a comprehensive set of guidelines and user requirements aimed at guiding the design and implementation of Autonomous Vehicle (AV) pilot sites. The focus group sessions engaged 17 participants from diverse backgrounds, uncovering a wealth of insights into user needs and preferences. The analysis identified several key themes—psychological perspectives, diverse user representation, social perspectives, affective perspectives, context of use, user experience factors, and evaluation criteria—that encapsulate the critical concerns and expectations of potential users.

Each theme was explored in depth, revealing specific requirements that must be met to ensure the success and inclusivity of AV technologies. Each guideline is rooted in the key themes and insights identified during the qualitative analysis, reflecting the participants' experiences and perspectives. For instance, psychological perspectives highlighted the importance of trust and transparency in AV operations, while diverse user representation underscored the need for designs that cater to users of various ages, abilities, and socio-economic backgrounds. Social perspectives emphasized the role of AVs in facilitating interactions among passengers, while affective perspectives revealed the emotional responses users experience when engaging with AVs, such as anxiety or excitement.

The context of use was also crucial, with discussions indicating that user requirements may vary significantly depending on whether AVs are employed for public transport, private commuting, or in specialized services for individuals with disabilities. User experience factors encompassed usability, comfort, and safety, all of which are vital for user acceptance and satisfaction. Lastly, the evaluation criteria established the benchmarks against which the success of AV technologies can be assessed, ensuring ongoing alignment with user needs.

The following guidelines and requirements have been crafted to align with these themes, providing a structured approach to creating user-centered, accessible, and adaptable AV systems. These guidelines not only aim to enhance user experience but also seek to promote the inclusivity and safety of AV services, ensuring they resonate with a diverse user base. The structured recommendations will facilitate the design and implementation processes by prioritizing user feedback, thereby fostering an environment where AV technologies can thrive and become integral components of modern mobility solutions. Guidelines and user requirements extraction.

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6.1.1. Psychological Perspectives

Guideline: Build Trust and Transparency in Technology

- The AV system must include transparent communication features that provide users with real-time updates on the vehicle's decisions and actions. This could be achieved through a clear, user-friendly interface that explains why certain manoeuvres are made, particularly in complex or unexpected situations.
- Implement an easily accessible feedback mechanism where users can report their experiences and concerns, ensuring that trust in the system is maintained and enhanced over time.

Guideline: Ensure Perceived and Actual Safety

- The AV must include multiple safety features, such as real-time monitoring, collision avoidance systems, and emergency stop functions. These features should be clearly visible and easily accessible to users to provide a sense of security.
- Safety protocols should be communicated to users upon entry, including demonstrations or tutorials on how to use safety features, ensuring that all passengers feel secure throughout the ride.

Guideline: Address Ethical Concerns

- Connected and Autonomous Vehicle (CAV) systems should implement transparency strategies to inform users about data collection practices that may pose privacy risks, such as data tracking and storage policies.
- The behavior of CAV systems must align with fundamental ethical and legal principles. AV systems should adhere to principles of honesty, fairness, transparency, respect for user autonomy, and social responsibility.
- AV systems should prioritize data privacy and ethical decision-making algorithms that align with societal norms. This includes ensuring that any data collected from users is anonymized, securely stored, and used transparently.
- Ethical decision-making protocols (e.g., in potential collision scenarios) should be clearly outlined and communicated to users to build confidence in the vehicle's judgment.

6.1.2. Social Perspectives

Guideline: Facilitate Optional Social Interaction

- Design AV interiors to accommodate both social interaction and privacy. This can be achieved through adjustable seating arrangements that allow passengers to face each other if desired, or to opt for a more private setup.
- Implement features that encourage optional social engagement, such as interactive displays or games, while also allowing passengers to opt-out and enjoy a quiet, private ride.

Guideline: Respect Privacy and Personal Space

- Provide personal space indicators, such as partitions or adjustable seating, to give passengers control over their level of interaction. Ensure that any interactive features are non-intrusive and can be easily disabled.
- AVs should include privacy controls, such as the ability to mute intercoms or disable shared screens, ensuring that passengers can enjoy their ride without unnecessary disturbances.

6.1.3. Diverse User Representation

Guideline: Ensure Physical Accessibility for All Users

- AVs design should proactively promote inclusivity by avoiding discrimination against individuals or groups and by not creating or reinforcing widespread social inequalities among users. Additionally, the use of inclusive language should be adopted.
- AVs must be equipped with accessible features such as ramps or lifts for wheelchair users, spacious interiors for assistive devices, and clearly marked, easy-to-reach controls. These features should be seamlessly integrated into the vehicle's design.
- Regular testing and updates of accessibility features should accommodate a wide range of physical disabilities, ensuring that all users can enter, exit, and move within the vehicle comfortably and independently.

Guideline: Prioritize Digital Accessibility

- The AV system's digital interfaces, including apps and in-vehicle controls, must be fully accessible to users with visual, auditory, and cognitive impairments. This includes voice commands, screen readers, and simplified navigation options.
- Offer multiple formats of information (visual, auditory, and tactile) to cater to different needs, ensuring that all users can easily access and understand the system's features and functions.

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6.1.4. Affective Perspectives

Guideline: Enhance Emotional Comfort and Reduce Anxiety

- The design of AVs should include features that positively influence users' emotional responses, such as ambient lighting, comfortable seating, and smooth ride dynamics. These elements can help reduce anxiety and enhance overall comfort.
- Implement real-time reassurance mechanisms, such as notifications or voice prompts that inform users of what the vehicle is doing and why, especially during unusual or unexpected manoeuvres.

Guideline: Address Physical Discomfort Proactively

- Incorporate motion sickness prevention features, such as adaptive suspension systems, air filtration, and adjustable seating, to enhance physical comfort during the ride.
- Provide users with options to adjust environmental controls, such as air conditioning and seat positions, to mitigate discomfort and enhance their overall experience.

6.1.5. Context of Use

Guideline: Adapt Features Based on Usage Context

- AVs should be adaptable to different contexts, such as urban versus rural settings, and public versus private transportation. This might include different navigation modes, speed adjustments, and route options tailored to specific environments.
- Context-sensitive features should automatically adjust based on the vehicle's usage scenario, such as enhanced privacy in private rides or flexible seating arrangements in public transportation settings.

Guideline: Ensure Flexibility for Various Service Types

- The AV system should be able to switch between different service types (e.g., fixed schedule vs. on-demand) and provide real-time updates and options for users, such as route changes or waiting times.
- Implement robust scheduling and routing algorithms that optimize the AV's performance based on the specific service context, ensuring punctuality and efficiency in all scenarios.

6.1.6. User Experience Factors

Guideline: Prioritize Safety and Accessibility

- Safety and accessibility should be the top priorities in the AV design, with all features evaluated against these criteria to ensure they meet the highest standards.
- Regularly update safety and accessibility protocols based on user feedback and technological advancements, ensuring that the AV remains responsive to evolving user needs.

Guideline: Enhance Comfort and Usability

- Design the AV to offer a high level of comfort, with ergonomic seating, intuitive controls, and personalized environmental settings. Ensure that these features are easy to use for all passengers, regardless of their technical proficiency.
- Continuously gather user feedback on comfort and usability and use this information to make iterative improvements to the vehicle's design and features.

6.1.7. Evaluation Criteria

Guideline: Establish Comprehensive Evaluation Metrics

- Define clear evaluation criteria for pilot studies, including user acceptance, system usability, safety, inclusivity, and privacy. These criteria should be used to measure the success of the AV system in real-world conditions.
- Regularly assess the AV's performance against these criteria, adjusting as necessary to improve the overall user experience and system reliability.

Guideline: Incorporate User Feedback into Evaluation

- Include user feedback as a key component of the evaluation process, ensuring that the criteria reflect the actual experiences and needs of the users.
- Employ both qualitative and quantitative methods to gather comprehensive data during the pilot studies, allowing for a nuanced understanding of how the AV meets user requirements.

Guideline: Gender balance

- It is crucial to integrate diversity into every aspect of CAV system and service design, encompassing gender and other socially relevant dimensions. Engaging a balanced demographic in user testing and focus groups will ensure the needs and preferences of all genders are appropriately addressed in the AV design and functionality.

6.2. Evaluation protocol and checklist

This evaluation protocol and checklist are designed to guide the implementation and assessment of pilot sites for Autonomous Vehicles (AVs). It ensures that the pilot sites adhere to User-Centered Design (UCD) principles, addressing key themes such as psychological perspectives, social interactions, accessibility, safety, and overall user experience. Each theme includes specific criteria to be evaluated, ensuring that the pilot sites meet the highest standards of usability, inclusiveness, and performance.

6.2.1. Psychological Perspectives

Objective:
To ensure that the AV system builds trust and transparency, maintains user safety and security, and addresses ethical concerns.

Checklist Criteria:

- **Trust and Transparency:**
    - Does the AV provide clear and accessible information about its decision-making processes?
    - Are there real-time updates that communicate the vehicle's actions and the reasons behind them?
    - Is there a feedback mechanism for users to report experiences and concerns?
- **Safety and Security:**
    - Are safety features such as emergency stop functions and collision avoidance systems clearly visible and easily accessible?
    - Are safety protocols effectively communicated to users upon entry?
- **Ethical Considerations:**
    - Does the system prioritize data privacy, with proper consent and protection measures in place?
    - Are ethical decision-making protocols clearly outlined and communicated to users?

Evaluation Method:

- **User Testing and Feedback Analysis:** Conduct user testing sessions with diverse participants, simulating real-world scenarios to observe interactions with the AV system. Gather feedback through structured interviews and surveys focusing on trust, safety, and ethical concerns.
- **System Log Monitoring:** Monitor system logs to assess how the AV communicates its decisions in real-time and the frequency of user interactions with safety features.
- **Ethics Review:** Ensure all data privacy measures comply with relevant regulations, and that ethical decision-making processes are transparent and well-communicated to users.

6.2.2. Social Perspectives

Objective:

To facilitate optional social interaction while respecting privacy and personal space.

Checklist Criteria:

- **Facilitating Interaction:**
  - Does the AV design allow for adjustable seating arrangements to facilitate or discourage social interaction?
  - Are there non-intrusive features available that encourage optional social engagement?
- **Privacy and Personal Space:**
  - Are there options for passengers to maintain privacy and control over their personal space?
  - Can users easily disable or opt out of interactive features?

Evaluation Method:

- **Behavioural Observation:** During pilot runs, observe passenger behaviour to document how often and in what ways users engage socially. Assess whether the seating arrangement and interactive features encourage or inhibit social interaction.

- **Post-Ride Surveys:** Distribute surveys after the ride to gather feedback on comfort and privacy. Questions should assess whether users felt they had sufficient control over their social and private space.
- **Focus Groups:** Conduct focus groups to delve deeper into user preferences for social interaction and privacy. Use these discussions to refine AV features that balance social engagement and privacy.

6.2.3. Diverse User Representation

Objective:
To ensure that the AV system is accessible to all users, including those with disabilities, and that digital interfaces are inclusive.

Checklist Criteria:

- **Physical Accessibility:**
  - Is the AV equipped with features like ramps or lifts for wheelchair users and sufficient space for assistive devices?
  - Are accessibility features seamlessly integrated and easy to use?
- **Digital Accessibility:**
  - Are digital interfaces accessible to users with visual, auditory, or cognitive impairments?
  - Does the system offer multiple formats for information delivery (e.g., visual, auditory, tactile)?

Evaluation Method:

- **Inclusive User Testing:** Engage participants with various disabilities in the testing phases to ensure that both physical and digital accessibility features meet their needs.
- **Usability Testing with Assistive Devices:** Test the AV with commonly used assistive devices (e.g., screen readers, voice control) to ensure compatibility and ease of use.
- **Expert Review:** Involve accessibility experts to review the design and implementation of accessibility features. They should provide feedback on both the physical environment and digital interfaces.
- **Feedback Collection:** Use interviews and surveys to gather detailed feedback from participants with disabilities on their experience with both physical and digital accessibility features.

6.2.4. Affective Perspectives

Objective:

To enhance emotional comfort, reduce anxiety, and address physical discomfort during the ride, thereby promoting long-term user satisfaction.

Checklist Criteria:

- **Emotional Comfort:**
  - Does the AV include features such as ambient lighting, comfortable seating, and smooth ride dynamics that contribute to sustained emotional well-being?
  - Are real-time reassurance mechanisms (e.g., notifications, voice prompts) in place to inform users of the vehicle's actions, helping to maintain a sense of security throughout the ride?
- **Physical Discomfort and Motion Sickness:**
  - Are motion sickness prevention features included in the vehicle design to enhance overall comfort during prolonged use?
  - Can users easily adjust environmental controls, such as air conditioning and seat positions, to suit their preferences also during long-term use?

Evaluation Method:

- **Physiological Monitoring:** Use wearable sensors (e.g., heart rate monitors, galvanic skin response sensors) during test rides to measure physiological indicators of stress or discomfort over time.
- **Real-Time Feedback Mechanisms:** Incorporate real-time user feedback mechanisms (e.g., buttons or voice commands) to allow users to report discomfort immediately.
- **Post-Ride Interviews:** Conduct detailed interviews post-ride to understand the emotional and physical experience of users. Focus on specific factors such as the effectiveness of ambient lighting, seating comfort, and the impact of reassurance mechanisms on reducing anxiety, thereby assessing long-term user satisfaction.
- **Comfort Simulations:** Simulate long-duration rides to assess the cumulative effect of physical discomfort and motion sickness and gather feedback on possible adjustments to environmental controls.

6.2.5. Context of Use

Objective:

To ensure that the AV system adapts to different usage contexts.

Checklist Criteria:

- **Adaptation to Usage Context:**
  - Does the AV system offer navigation modes, speed adjustments, and route options tailored to different environments?
  - Are context-sensitive features implemented to optimize the vehicle's performance?
- **Flexibility for Service Types:**
  - Can the AV switch between different service types (fixed schedule vs. on-demand) and provide real-time updates to users?
  - Are scheduling and routing algorithms robust enough to ensure punctuality and efficiency?

Evaluation Method:

- **Service Type Simulation:** Simulate different service types (e.g., fixed schedules, on-demand services) to evaluate the AV's flexibility and performance.
- **Real-Time Data Monitoring:** Monitor real-time data during these tests to assess how the AV adjusts navigation modes, speed, and route options.
- **User Feedback Surveys:** After each context-specific test, collect feedback from users to understand their satisfaction with the AV's performance in different environments.
- **Comparative Analysis:** Compare the performance metrics across different contexts to identify any weaknesses in the AV's adaptability and make necessary adjustments.

6.2.6. User Experience Factors

Objective:
To prioritize safety, accessibility, comfort, usability and inclusivity in the design of the AV system.

Checklist Criteria:

- **Safety and Accessibility:**
  - Are safety and accessibility consistently prioritized in the design?
  - Are these aspects regularly updated based on user feedback and technological advancements?
- **Comfort and Usability:**
  - Does the AV offer high levels of comfort, with ergonomic seating, intuitive controls, and personalized settings?

  - Is user feedback on comfort and usability continuously gathered and used for iterative improvements?

Evaluation Method:

- **Comprehensive Usability Testing:** Perform usability testing with a diverse user base to evaluate safety, accessibility, comfort, overall usability, and inclusivity.
- **Feedback Implementation:** Establish continuous feedback where users can report issues or suggest improvements and ensure that this feedback is reviewed and updated regularly.
- **Iterative Design Updates:** Based on the feedback and testing results, iteratively update the design to address any identified issues.
- **Long-Term Usability Study:** Conduct long-term studies to evaluate how the usability, comfort and inclusivity of the AV evolve over time and with repeated use.
- **KPI Tracking and Analysis:** Develop a set of Key Performance Indicators (KPIs) for each aspect of the AV's performance (e.g., user acceptance, safety, inclusivity) and track these KPIs throughout the pilot phase.
- **Mixed-Methods Approach:** Use a mixed-methods approach (e.g., combining surveys, interviews, and observation) to gather comprehensive data on user experiences.

7. Challenges in the Development of Inclusive Autonomous Systems: The AutoTRUST Approach

The AutoTRUST project is centered on overcoming critical challenges in developing autonomous, self-adaptive services for mobility, with a focus on enhancing user inclusiveness, personalization, and resilience. The state-of-the-art review reveals several technological, social, and human-centered barriers that must be addressed to achieve these goals. The following challenges have been identified as focal points of the AutoTRUST project, each demanding a multidisciplinary approach that integrates cutting-edge AI, HCI, and advanced vehicle technologies.

AVs rely on multimodal sensing technologies such as cameras, LiDAR, and GNSS to navigate complex environments. However, despite significant advancements in individual sensor technologies, challenges persist in achieving cooperative 4D situational awareness. Current approaches to V2X communication face issues related to data fusion and the interpretation of sensor data across diverse environments. The uncertainty in sensor measurements is a major challenge, particularly when AVs must make decisions in real-time in dynamic environments. FL offers a promising approach to address these concerns, enabling distributed vehicles to collaborate while protecting user privacy and optimizing their local models. However, the computational and communication overhead introduced by FL remains a significant challenge. AutoTRUST aims to develop a trustworthy, data-driven localization architecture that enhances cooperative situational awareness. The project seeks to reduce the communication costs and privacy risks associated with traditional collaborative localization techniques. Moreover, AutoTRUST aims to mitigate discomforts such as motion sickness and improve overall passenger safety and comfort.

Another major challenge in developing inclusive autonomous vehicles lies in ensuring that the system can adapt to the diverse needs of different users, including people with disabilities, the elderly, and other vulnerable populations. The state-of-the-art in personalized adaptation technologies, such as adaptive climate control and seating adjustments, has made strides toward enhancing user comfort. However, these systems often fail to anticipate user needs in real-time, particularly in unexpected or dynamic situations. AutoTRUST aims to extend current adaptive systems by incorporating advanced multimodal sensors and AI-based monitoring systems that can adjust the vehicle's interior environment. This requires developing solutions that can seamlessly adapt to a user's emotional state, cognitive load, and accessibility needs without compromising the system's reliability or safety.

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As AVs collect vast amounts of data to enhance safety and user experiences, the privacy and security of this data pose significant challenges. Cybersecurity risks, including unauthorized access to sensitive user data and cyber-physical attacks on vehicle systems, have emerged as pressing concerns. The state-of-the-art in securing AV systems has focused on encryption techniques and anomaly detection systems, but these methods must evolve to address increasingly sophisticated threats. AutoTRUST addresses these concerns by ensuring that user data remains private while allowing for adaptation. Additionally, the project focuses on developing a robust framework for ethical data use, ensuring compliance with global data protection regulations and fostering public trust in autonomous systems. The ethical challenges surrounding transparency in AI decision-making and the potential for bias in AV systems are also at the forefront of the project's research objectives.

Building user trust in AVs is one of the most critical challenges for widespread adoption. Users are often hesitant to trust AV systems due to decision-making processes and concerns about vehicle control during emergencies. AutoTRUST aims to overcome these barriers by utilizing Human-centered design methodologies, such as UCD, improving the intuitiveness and usability of AV systems. The project's focus on user needs will help reduce their anxiety and improve the overall driving experience. Additionally, by developing a robust framework for evaluating user trust and comfort, AutoTRUST will ensure that its solutions align with the diverse psychological and emotional needs of passengers.

8. Conclusion

The AutoTRUST project embodies a pioneering approach to the development of autonomous, self-adaptive mobility services that emphasize inclusiveness, personalization, and resilience. This document has set a solid foundation by synthesizing state-of-the-art technologies, integrating detailed user requirements, and rigorously applying a User-Centered Design (UCD) methodology. This approach has been instrumental in shaping a framework for developing Autonomous Vehicle (AV) solutions that are not only technologically advanced but also highly responsive to user needs, particularly among diverse demographic groups and vulnerable populations.

The project’s strategic orientation leverages multimodal technologies, human-centered design principles, and iterative feedback loops, ensuring that AVs can accommodate and adapt to the complex needs of end users. Inclusiveness is prioritized throughout the design and development process, with a deliberate focus on accessibility and safety. This is achieved by considering psychological, social, and physical factors that affect user interaction with AVs, as demonstrated in focus group sessions that have informed key design elements such as trust, accessibility, social usability, and cognitive load management. To achieve a nuanced understanding of user requirements, the UCD methodology included comprehensive focus group sessions that engaged 17 participants with diverse backgrounds and experiences. These participants, representing a mix of age groups, professions, and levels of familiarity with AVs, provided valuable insights into key aspects of AV use, such as trust, safety, accessibility, and social and affective responses to autonomous travel. The focus group discussions highlighted critical user concerns and preferences, which were systematically analyzed and integrated into the design guidelines. This user feedback has shaped the AV system design guidelines to reflect real-world user experiences, thus aiming for AV solutions that exceed expectations in reliability, safety, and accessibility.

Looking forward, the next milestones will concentrate on collaborating with developers to implement the user requirements and design guidelines outlined in this document. This includes refining the AV system architecture and validating proposed solutions in real-world pilot sites, where feedback will be gathered to inform further enhancements. Key Performance Indicators (KPIs) will be used to measure project success, focusing on technical performance, ethical considerations, and user satisfaction. These KPIs will provide a structured framework to ensure that AutoTRUST's AV solutions meet the highest standards of functionality and user-centered design. Moreover, future work will also incorporate quantitative data collection methods, such as Likert scale surveys, to facilitate comparisons between different focus groups and specific categories of users. By integrating these quantitative measures, we can gain a clearer understanding of user preferences and experiences, enabling more robust analysis of the feedback re-

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ceived. This quantitative approach will not only enhance the reliability of our findings but also assist in prioritizing the key topics discussed by participants, ultimately guiding the development of targeted interventions and improvements in technology design.

This document not only establishes the foundational principles and strategic direction for the project but also serves as a roadmap for ongoing innovation, testing, and improvement. The continued collaboration among consortium partners and stakeholders is crucial to achieving the project's vision of transformative, user-centered autonomous mobility solutions that set new benchmarks in inclusivity and user trust.

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Annexes

Annex A User Feedback Survey example

A.1. Questionnaire

Introduction:

Thank you for participating in this autonomous vehicle pilot study. This survey is designed to gather feedback on your experience, focusing on trust, safety, and transparency. Please respond to the following statements by selecting how much you agree or disagree with each one.

Scale:

- **Strongly Disagree (1)**
- **Disagree (2)**
- **Neutral (3)**
- **Agree (4)**
- **Strongly Agree (5)**

1. Trust in the AV System

I felt confident that the AV could navigate through traffic safely.

[ ] 1 – Strongly Disagree
[ ] 2 – Disagree
[ ] 3 – Neutral
[ ] 4 – Agree
[ ] 5 – Strongly Agree

I trusted the AV to make decisions in unexpected situations (e.g., obstacles, sudden braking).

[ ] 1 – Strongly Disagree
[ ] 2 – Disagree
[ ] 3 – Neutral
[ ] 4 – Agree
[ ] 5 – Strongly Agree

I felt in control throughout the ride, even though the vehicle was autonomous.

[ ] 1 – Strongly Disagree
[ ] 2 – Disagree
[ ] 3 – Neutral

[ ] 4 – Agree
[ ] 5 – Strongly Agree

I would feel comfortable riding in an AV again based on this experience.
[ ] 1 – Strongly Disagree
[ ] 2 – Disagree
[ ] 3 – Neutral
[ ] 4 – Agree
[ ] 5 – Strongly Agree

2. Safety Perception

I felt safe throughout the entire ride in the AV.
[ ] 1 – Strongly Disagree
[ ] 2 – Disagree
[ ] 3 – Neutral
[ ] 4 – Agree
[ ] 5 – Strongly Agree

The safety features (e.g., seat belts, emergency stop buttons) were clearly visible and accessible.
[ ] 1 – Strongly Disagree
[ ] 2 – Disagree
[ ] 3 – Neutral
[ ] 4 – Agree
[ ] 5 – Strongly Agree

The AV's movements (e.g., braking, acceleration, turning) were smooth and made me feel secure.
[ ] 1 – Strongly Disagree
[ ] 2 – Disagree
[ ] 3 – Neutral
[ ] 4 – Agree
[ ] 5 – Strongly Agree

I felt that the AV could handle emergencies or sudden changes in traffic conditions safely.
[ ] 1 – Strongly Disagree
[ ] 2 – Disagree

[ ] 3 – Neutral
[ ] 4 – Agree
[ ] 5 – Strongly Agree

3. Transparency of the AV System

The AV provided me with enough information about its actions (e.g., stopping, changing lanes).
[ ] 1 – Strongly Disagree
[ ] 2 – Disagree
[ ] 3 – Neutral
[ ] 4 – Agree
[ ] 5 – Strongly Agree

I understood why the AV was making certain decisions during the ride (e.g., slowing down, stopping).
[ ] 1 – Strongly Disagree
[ ] 2 – Disagree
[ ] 3 – Neutral
[ ] 4 – Agree
[ ] 5 – Strongly Agree

I felt reassured by the AV’s feedback (e.g., voice prompts, screen updates) during the ride.
[ ] 1 – Strongly Disagree
[ ] 2 – Disagree
[ ] 3 – Neutral
[ ] 4 – Agree
[ ] 5 – Strongly Agree

I would have preferred more information from the AV system while it was driving.
[ ] 1 – Strongly Disagree
[ ] 2 – Disagree
[ ] 3 – Neutral
[ ] 4 – Agree
[ ] 5 – Strongly Agree

4. Overall Experience

My overall experience with the AV was positive.

[ ] 1 – Strongly Disagree

[ ] 2 – Disagree

[ ] 3 – Neutral

[ ] 4 – Agree

[ ] 5 – Strongly Agree

I would recommend using an AV to others based on my experience.

[ ] 1 – Strongly Disagree

[ ] 2 – Disagree

[ ] 3 – Neutral

[ ] 4 – Agree

[ ] 5 – Strongly Agree

5. Additional Feedback

Please provide any additional comments or suggestions for improving the AV system below: