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

D4.1 Human Factors and Adaptation.v1

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List of acronyms and abbreviations

Abbreviation	Description
ADV	Autonomous Delivery Vehicle
AI	Artificial Intelligence
API	Application Programming Interface
AV	Autonomous Vehicle
CAV	Connected and Automated Vehicle
DAG	Directed Acyclic Graph
DOI	Disclosure of Others' Information
EEG	Electroencephalogram
EU	European Union
GDPR	General Data Protection Regulation
HCI	Human–Computer Interaction
HMI	Human–Machine Interface
HRV	Heart Rate Variability
ICV	Intelligent Connected Vehicle
IDP	Interdependent Privacy
IPN	Interdependent Privacy Nudge
ITU	Intention To Use
KPI	Key Performance Indicator
NDRT	Non-Driving-Related Task
OSN	Online Social Network
PoDaR	Potential Damage Risk model
QoE	Quality of Experience
QoS	Quality of Service
SAE	Society of Automotive Engineers
SAV	Shared Autonomous Vehicle
SCR	Skin Conductance Response
SEM	Structural Equation Model
SIoV	Social Internet of Vehicles
UI	User Interface
UCD	User Centered Design
UTAUT2	Unified Theory of Acceptance and Use of Technology 2
UX	User Experience

Abbreviation	Description
VAS	Virtual Assistant System
WP	Work Package

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Executive Summary

This deliverable (D4.1) sets out the conceptual and technical foundations for adaptive personalization in Connected and Automated Vehicles (CAVs). It integrates user needs and traits identified in WP2, adaptation logic developed in WP4, and validation activities in WP5 into a unified framework that balances personalization, inclusiveness, and resilience.

Personalization services, supported by multimodal cabin sensing, promise enhanced passenger experience and comfort. Yet, their deployment in shared settings introduces challenges: data collection may extend beyond the initiating passenger, raising questions of fairness, transparency, and compliance with privacy principles. These risks are part of a broader landscape of acceptance barriers that must be addressed to ensure trust in automated mobility.

A central focus of D4.1 is risk perception. Both physiological monitoring (e.g., HRV, SCR, EEG) and self-report studies demonstrate that perceived risks, including safety, cybersecurity, privacy, and performance, strongly influence trust and acceptance of CAVs. By consolidating existing literature and introducing new modelling approaches, this deliverable provides empirical evidence that risk perception is a decisive factor in adoption.

The work contributes to AutoTRUST's objectives by:

- **Integration Across Work Packages:** Clarifies how WP2 user needs, WP4 adaptation logic, and WP5 validation activities connect in a unified flow diagram, ensuring transparency and traceability across the project.
- **Consolidated Risk Perception Models:** Harmonises fragmented literature into a structured taxonomy of objective (physiological) and subjective (self-report) approaches, demonstrating how both jointly shape trust and acceptance in CAVs.
- **Framework for Privacy-Aware HMIs:** Translates human factors insights into machine-readable specifications, outlining technical requirements for adaptive, inclusive, and GDPR-compliant human–machine interfaces.
- **Contribution to Standards and Policy:** Aligns findings with GDPR principles and EU Ethics Guidelines for Trustworthy AI, ensuring relevance to ongoing regulatory and standardization efforts.

1. Introduction

Deliverable D4.1 “Human Factor and Adaptation.v1” represents the first comprehensive effort within the project to consolidate and articulate research findings related to human factors, adaptation, and personalization in automated mobility systems. As an initial release, it serves as both a reference and a guideline for consortium members, outlining the principles, methodologies, and preliminary results that will inform subsequent development and validation of activities across the project.

The document emphasizes the central role of human factors in the design and deployment of Connected and Automated Vehicles (CAVs), recognizing that user trust, acceptance, and perceived safety are as critical to successful adoption as technological reliability. It gathers early insights from ongoing studies examining how individuals perceive, interact with, and adapt to automated systems, as well as how those systems can, in turn, adapt to users. Topics such as trust calibration, cognitive workload, risk perception, emotional responses, and user experience form the core of this initial analysis, providing a foundation for human-centered innovation.

A key focus of D4.1 lies in exploring adaptation and personalization methods. These include approaches such as user profiling, in-cabin behaviour monitoring, and adaptive interface design, all aimed at creating vehicle environments that dynamically respond to the preferences, needs, and contextual states of passengers. By integrating these elements, the deliverable highlights pathways to enhance comfort, inclusiveness, and trust to ensure trustworthy interaction between humans and automated systems.

In essence, D4.1 provides the conceptual groundwork for embedding human-centric considerations within the project’s technical and experimental work. It establishes a shared understanding of the factors influencing user behaviour and system adaptation, setting the stage for more detailed analyses and demonstrator-level applications in future iterations of the deliverable.

1.1. Purpose and Structure of the Document

The purpose of the AutoTRUST “Human factor and adaptation.v1” is to record the project’s initial research findings on human factors, as well as on adaptation and personalization strategies in the context of automated mobility. This first version provides a structured overview of early insights into user perception, behaviour, and interaction with automated systems, establishing a baseline for ongoing research and consortium activities.

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Additionally, the deliverable highlights preliminary approaches to adaptation and personalization, including user-tailored interfaces. By documenting these early results, the deliverable provides consortium members with a shared reference framework, ensuring that subsequent development and experimentation are guided by evidence-based understanding of human needs, preferences, and expectations in the AutoTRUST ecosystem.

The structure of this deliverable, based on the current content, is presented as follows:

- **Section 1 – Introduction**: Outlines the purpose, intended audience, and interrelations of D4.1 within the AutoTRUST project.
- **Section 2 – Human-Centered Research**: Presents foundational research activities, including surveys, interviews, and stakeholder engagement (WP2), behavioural cues for in-cabin adaptation, and the interdependent privacy problem in shared cabins.
- **Section 3 – Human Factor Taxonomy for In-Cabin Adaptation**: Defines human trait categories, introduces personas, and addresses ethics and vulnerable user profiles.
- **Section 4 – Mapping to Personalization Triggers**: This maps human traits to personalization triggers, including adaptation flows and inclusive design considerations.
- **Section 5 – Conclusions**: Summarizes findings and outlines directions for future work across consortium partners.
- **Section 6 – References**: Provides bibliographic sources supporting the analyses.

1.2. Indented Audience

The AutoTRUST D4.1 "Human Factor and Adaptation.v1" is devised for public use as well as for the AutoTRUST consortium, including project partners, affiliated stakeholders, and external audiences interested in advancements in human factors, adaptation, and personalization in automated mobility systems. This document mainly focuses on the algorithms, tools, and methods for human factors and in-cabin adaptation, thereby serving as a referential tool throughout the project's lifespan.

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 15 partners from 10 EU member states and associated countries

(Switzerland, United States, and Korea), 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 categorised 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 communication amongst the consortium of 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). Deliverable D4.1: Human Factor and Adaptation.v1 is a key output of Work Package 4 (WP4): Intelligent Personalisation, Adaptation and Virtual Assistant System (VAS). It relies on the foundational user-centered requirements and architectural specifications defined in D2.2 (Specifications and architecture design.v1), which is a key deliverable of WP2. D4.1 documents the initial framework for machine-readable human factors, which represents a crucial set of system results, combined with the results of WP3 (Advanced Monitoring system (AMS) and Data Processing) that are subsequently slated for validation and evaluation during WP5 pilots (Framework Integration, Validation and Evaluation).

2. Human-Centered Research

Cyber-Physical Systems (CPSs) comprise digital software platforms, physical infrastructure, and human components [1]. CAVs are a subset of CPSs and have gained significant traction, promising to enhance transportation efficiency, improve safety, and alleviate environmental damage, among other potential benefits [2]. CAVs consist of Autonomous Vehicles (AVs) and Connected Vehicles (CVs), leveraging their respective benefits synergistically [2]. The Society of Automotive Engineers (SAE) defines six levels of driving automation, ranging from 0 (fully manual) to 5 (fully autonomous) [3]. Levels 3, 4, and 5 are particularly relevant for this work as they involve the vehicle performing most driving tasks, allowing occupants to engage in non-driving related tasks (NDRTs) [4].

The full societal and commercial potential of CAVs is expected to be realised through their integration with shared mobility services [5, 6]. Shared CAVs refer to vehicles used by multiple individuals or groups, simultaneously or sequentially, often involving agreements to share space for part or all of a journey through on-demand transportation service offerings [7]. They are categorized based on vehicle size (micro-, small, mid-sized, and large) and sharing structure [8]. The three main sharing structures include car-sharing (a single user served per request), ridesharing (two or more users sharing the same trip), and hybrid combinations of these models [9]. As CAV technologies evolve, their societal impact is shaped not only by their technical performance but also by how they integrate into broader mobility ecosystems. While international frontrunners such as the United States and China have already initiated large-scale deployments of Level 4 shared CAVs [10], Europe follows a distinct trajectory influenced by its regulatory environment and emphasis on inclusiveness and user trust. Within this context, emerging European initiatives, including AutoTRUST, increasingly prioritize human-centered design and AI-driven personalization, enabled by advanced multimodal environmental and physiological sensors. To ensure that AutoTRUST's technological developments remain aligned with real-world user needs, WP2 plays a crucial role in leading surveys, interviews, and stakeholder engagement activities that build the project's user-driven foundation.

As CAV technologies evolve, their societal impact is shaped not only by their technical performance but also by how they integrate into broader mobility ecosystems. While international frontrunners such as the United States and China have already initiated large-scale deployments of Level 4 shared CAVs [10], Europe follows a distinct trajectory influenced by its regulatory environment and emphasis on inclusiveness and user trust. Within this context, emerging European initiatives, including AutoTRUST, increasingly prioritize human-centered design and AI-driven personalization, enabled by advanced multimodal environmental and physiological sensors.

2.1. WP2: Surveys, Interviews, and Stakeholder Engagement

Building on the substantial body of work already established through WP2, the next phase of activities related to surveys, interviews, and stakeholder engagement will further expand and consolidate the user-driven foundation of the project. The previous deliverable demonstrated the value of structured engagement through multiple focus groups, involving experts, older adults, individuals with disabilities, visually impaired users, and the general public. These interactions provided rich qualitative insights into user expectations, accessibility needs, safety perceptions, and emotional and social factors influencing trust in autonomous mobility. Throughout this phase, a combination of focus groups, exploratory discussions, and preparatory survey activities were carried out across partner regions, with a particular emphasis on understanding the needs of diverse and often underserved user groups. These interactions formed a core component of the user requirements analysis and informed the refinement of the User Centered Design (UCD) methodology [11]. The work included multiple rounds of focus groups involving experts, individuals with disabilities, visually impaired and blind users, older adults, and members of the general public. Each group contributed distinct insights into the challenges and expectations associated with autonomous mobility. The sessions organised with participants with disabilities, as well as those conducted with blind and visually impaired users, provided particularly detailed accounts of the barriers encountered in current mobility systems and of the specific forms of support needed for safe, independent, and comfortable travel. These findings helped identify critical accessibility needs related to navigation, multimodal communication, environmental awareness, and trust-building mechanisms within autonomous vehicles.

Similarly, the engagement of older adults revealed concerns linked to safety, ease of use, clarity of information, and emotional comfort when interacting with automated systems. Through semi-structured dialogues, participants highlighted the importance of intuitive interfaces, predictable system behaviours, and clear feedback, underscoring the necessity of designing HMIs and virtual assistants that accommodate age-related sensory and cognitive changes. Expert stakeholders contributed complementary views that helped contextualise these user perspectives within broader technological, operational, and ethical frameworks.

Across all user categories, the focus groups followed protocols that ensured consistency in data collection while allowing space for open, qualitative exploration. These protocols included structured discussion guides, thematic prompts, and systematic documentation procedures. The sessions were complemented by an initial survey preparation process, in which thematic dimensions such as psychological, social, affective, contextual, and experiential were translated into measurable constructs that would later form the basis of the project's broader quantitative assessments.

The data collected through these activities were analysed thematically and served to refine the initial set of user requirements. The insights also supported the elaboration of inclusive design guidelines, highlighting the need for adaptive, personalized, and multimodal support systems capable of responding to heterogeneous user needs. The engagement work carried out by the involved partners thus constituted a central pillar, ensuring that the project's methodological framework and technical specifications remain grounded in real user experiences and aligned with the principles of accessibility, inclusiveness, and user trust.

2.2. Behavioural Cues for In-Cabin Adaptation

Recent research on autonomous vehicles underscores the growing importance of leveraging behavioural cues inside the cabin to enable adaptive, human-centered automation. While early AV safety architectures concentrated almost entirely on ensuring the technical integrity of the vehicle - through reliable sensing, redundant components, and fail-safe responses - recent research shows that this perspective is too narrow. As driving responsibility shifts from human to machine, the passenger's psychological and emotional experience becomes an integral part of overall safety. This means AVs must not only avoid mechanical or algorithmic failure but also be capable of perceiving and interpreting the human inside the cabin: their comfort level, stress, trust, understanding of the situation and expectations of how the vehicle should behave. Systems that can recognise behavioural and emotional cues such as facial expressions, posture, gaze, or vocal tone, can adapt their communication or driving style accordingly.

To address this, studies in affective computing and in-vehicle HMI show that AVs can interpret a wide range of cues such as facial expressions, gaze direction, posture changes, vocal tone, and even physiological signals, to infer a passenger's emotional and cognitive state [12] [13]. When these cues suggest discomfort or uncertainty, the vehicle can adapt in different ways: slowing down or smoothing its trajectory, increasing the clarity of its explanations, or adjusting the level of interaction to reassure the user. Research has shown that this kind of responsiveness directly supports trust, especially because trust in automation depends not just on performance, but on whether the system behaves in a way that feels predictable and aligned with human expectations [14] [15].

Work from the AV field also reinforces this direction. For example, the human-centred safety framework proposed by Kothinti et al. [16] emphasises that behavioural adaptation is key to bridging the gap between technical reliability and social acceptability. AVs that behave socially (signalling early, changing lanes smoothly, reacting to passenger tension) tend to reduce conflict and increase user confidence. At the same time, studies on explainable AI in autonomous driving show that clearer, more intuitive communication from the vehicle helps passengers make sense of AV decisions, especially in more complex or uncertain scenarios [17].

Within the AutoTRUST project, behavioural cues play a central role in designing an interior environment that can dynamically adapt to passengers' needs, comfort and safety. Leveraging in-cabin sensing capabilities, such as RGB and depth cameras, acoustic sensors, environmental sensors, and biometric measurements, combined with AI algorithms, the system is able to build a detailed understanding of the occupant's state. More specifically, the system can detect signs of stress, discomfort, drowsiness, distraction, and emotional state. Through WP3 and WP4, AutoTRUST develops machine-readable human-factor models and user profiles that capture physical, cognitive and behavioural characteristics, enabling personalized interior adjustments and explainable interactions via the Virtual Assistant. The project's adaptation objectives further support this by enabling automated configuration seats, lighting, climate and infotainment as well as alternative interaction methods (e.g., gesture control, joystick interfaces) to increase inclusiveness and comfort for diverse user groups. User-profile clustering can be used to identify groups of passengers who share similar behavioural patterns, comfort needs, motion sensitivity, or interaction preferences. These clusters allow the system to personalize in-cabin adaptations based on real, observed user characteristics, ensuring fair, inclusive, and context-aware personalization.

Such behavioural cues can drive a wide range of intelligent adaptations within AutoTRUST. Some examples include:

- **Automatic ergonomic adjustments,** such as adapting seat position, backrest angle, or headrest height when discomfort is detected.
- **Climate and air-quality regulation**, where temperature, airflow, humidity, and CO_2 levels are automatically adjusted if passengers show behavioural or physiological signs of drowsiness, fatigue, or irritation.
- **Motion sickness mitigation**, using personalized trajectory planning to smooth acceleration, cornering, and braking when behavioural cues such as frequent head movements or increased blinking indicate emerging discomfort.
- **Adaptive lighting**, where the interior lighting tone and intensity change based on cues such as slow blinking, eyelid drooping or unfocused gaze supporting alertness, reducing stress or creating a calmer environment.
- **Personalised infotainment adjustments**, such as lowering volume, modifying screen brightness, changing media type, or activating a "quiet mode" when passengers appear overwhelmed or fatigued.

- **Psychophysiological monitoring**, enabling the detection of drowsiness, distraction, or stress to trigger safety alerts or supportive interactions.
- **Dynamic cabin reconfiguration**, where seats, displays, and support elements adjust based on the user profile cluster (age, mobility constraints, behavioural patterns).

2.2.1. Shared Cabins, Personalization, and The Interdependent Privacy Problem

Personalization services are expected to be incorporated in both single and shared cabins and continuously rely on advanced cabin-scoped sensing technologies for their operation. This, however, creates an unforeseen, yet critical issue, particularly for the latter setting.

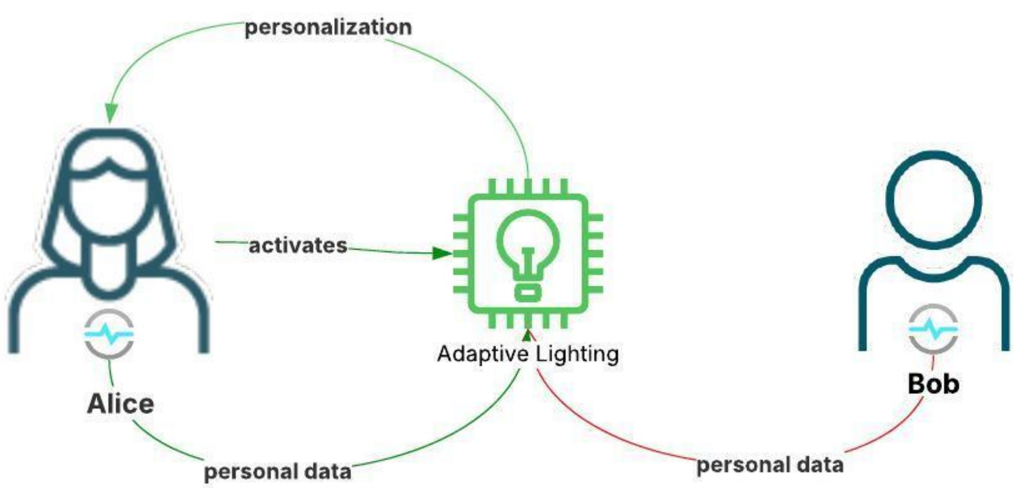

Figure 1: IDP in shared CAVs

Consider the following scenario (Figure 1):

- Let's imagine a passenger called Alice, enables an emotion-responsive lighting service on a shared automated bus; the service adapts cabin brightness to her emotional profile.
- The vehicle contains cabin-wide sensors, including cameras, contactless facial-EMG arrays, and gaze trackers that continuously record expressions and muscle-activity for all occupants.
- Although only Alice's computed emotional profile drives the lighting adjustments, the raw biometric signals from Bob, a co-passenger, are still captured by the sensors and retained by the vehicle system.

- Bob receives no prior in-ride notice and cannot prevent his biometric signals from being recorded without interrupting Alice's service.
- This removes Bob's ability to choose whether his biometric data is collected and processed. Thus, Alice's personalization causes involuntary collection and potential retention of Bob's sensitive biometric data.

In other words, as these personalization services utilize in-cabin multimodal sensors for data collection, activation by one or more passengers may result in the collection and processing of the physiological data of other passengers without their awareness or consent. These non-consenting co-passengers cannot enforce their rights to informational self-determination without interrupting the service(s) of the initiating passenger(s). In this context, privacy becomes interdependent rather than a matter of individual choice, where violations occur when co-passengers cannot control the processing of their personal or biometric data without restricting the initiating passengers' chosen service. This situation constitutes a violation of Interdependent Privacy (IDP), which is described as a breach in data privacy arising from the behaviour of other users within one's network [18]. Additionally, the data **perceived** to be involuntarily collected and processed goes beyond what is necessary to serve the service-initiating passenger(s), which potentially violates the GDPR principle of data minimization.

2.2.2. Limits of Individual Risk Models

Risk is typically expressed in terms of the likelihood and severity of adverse events occurring [19]. It encompasses several dimensions, the perception of which can influence user acceptance of (shared) CAVs, including cyber-attack, privacy, connectivity, performance, and safety [20]. Risk perception, therefore, refers to a psychological construct that captures how individuals interpret different forms of potential risks [21]. Risk perception can be assessed through complementary approaches. Objective methods leverage physiological indicators, such as Heart Rate Variability (HRV), Skin Conductance Responses (SCR), Electroencephalogram (EEG), to capture implicit arousal and affective states when occupants experience risky or intrusive scenarios [22]. Subjective methods rely on self-report instruments to capture the individual appraisal of risk that underpins acceptance decisions and trust formation [7].

The existing literature establishes that perceptions of risk (measured through both objective physiological signals and subjective self-reports) are critical barriers to the adoption of CAVs [1]. In this regard, we provide a sample of studies that model risk perceptions in subsequent sections.

2.2.3. Existing Literature on Real-Time Measurements of Risk Perceptions

Studies that rely on physiological indicators to measure different dimensions of perceived risk, include:

- **Physiological Signal Differentiation**: Perelló-March et al. [22] demonstrated that physiological signals differentiate between risk levels in SAE L3-4 vehicles: HRV captures low-to-moderate risk, while SCR responds to sudden, high-risk events. This work underscores the value of multimodal physiological monitoring for driver state assessment.
- **Personalised Risk Modeling**: Building on this, Chen et al. [23] quantified inter-individual differences using the Potential Damage Risk (PoDaR) model, showing that drivers maintain longer temporal risk horizons and safe spatial distances. Their findings highlight the need for personalised risk models to account for variability in human perception, which is essential for adaptive AV assistance systems.
- **Drowsiness & Alertness**: Perrotte et al. [24] extended these insights to drowsiness detection in Level-2 AVs, combining physiological and postural indicators. The study confirms that integrating multiple modalities improves the monitoring of driver alertness and safety.
- **Shared Control and Hazard Response**: Incorporating human perception into vehicle control enhances overall safety. Song et al. [8] proposed a human–machine shared lateral control strategy, where eye-tracking quantifies driver attention to dynamically allocate steering authority. Further, Ruiz et al. [4] examined occupant responses to unexpected hazards in Level-4 AVs, finding that pupil diameter revealed stronger perceived risk when the occupant's own safety was threatened, emphasizing the criticality of physiological responses even in fully automated contexts.
- **Predictive Risk Modeling and Cyber-Attacks**: Gandrez et al. [24] applied deep learning to successfully predict drivers' subjective risk perception, demonstrating the feasibility of personalised risk-aware AV systems. Finally, Ban [25] investigated responses to cyber-attacks while engaged in non-driving-related tasks (NDRTs), finding that NDRT engagement reduced situation awareness, highlighting the need for multimodal alert systems that account for cognitive load.

2.2.4. Existing Literature on Self-Report Measurements of Risk Perceptions

Existing works that rely solely on self-report measurements establish the subjective barriers to acceptance, include

- **Privacy and General Risk**: Kenesei et al. [20] found that privacy risk significantly negatively affects the Intention To Use (ITU) CAVs among the Hungarian population ($\beta=-0.17$). Similarly, Kapser and Abdelrahman [7] identified perceived general risk as one of the strongest predictors of acceptance of Autonomous Delivery Vehicles (ADVs) in Germany ($\beta=-0.173$).

- **Cybersecurity Concerns**: Focusing on SAE Level 5 AVs, Prasetio and Nurliyana [26] concluded that privacy and cybersecurity concerns were the most significant predictors of perceived safety ($\beta=0.482$, $p<0.001$). Passengers have also reported high willingness to pay for safeguards against communication failure and unauthorized personal data collection [27].
- **Cyber Barriers and Demographics**: Kinero et al. [28] found that older adults, individuals with lower education and income, and those with conservative ideologies perceive AVs as more vulnerable to cyber-attacks. Khan et al. [29] further found that perceptions of cyber-attacks amplify concerns about privacy, performance, and safety risks. In China, Feng et al. [30] found that risk perception reduced, while trust increased, pedestrians' propensity to cross streets.

Collectively, these studies address perceived risk stemming from the behaviour of the vehicle system itself or external actors, while neglecting those generated by the actions and choices of co-passengers in shared cabins. On the other hand, while some studies do in fact address co-passenger-induced perceptions of risk [31, 32], they tend to emphasize safety-related behaviours, paying little attention to risks emerging from privacy-related behaviours.

2.2.5. Existing Literature on Interdependent Privacy

This section reviews the extant literature on Interdependent Privacy (IDP) and justifies its role in the current climate of vehicular connectivity and automation. Privacy is defined by Westin [33] as the right to control, manage, and disclose information about oneself and decide when, how, and to what extent this information is communicated to others. Whereas IDP is predicated on the idea that the privacy of individuals depends on the privacy choices and actions of their connections [18].

A comprehensive survey by Humbert et al. [18] provided the foundational landscape, and subsequent studies have since contributed to the existing literature in several key domains (see Table 1: Existing Research in IDP

Author(s)	Method	Significant Results	IDP Domain
Franz and Benlian	Survey; Mediation analysis	IDP salience nudge makes users 62% less likely to disclose others' data.	Online Social Networks (OSNs)
Amon et al.	Surveys; Perception ratings	Identified IDP clusters (violators, preservers); Sharing likelihood inversely related to privacy.	OSNs

Author(s)	Method	Significant Results	IDP Domain
Wirth et al.	SEM on survey	Co-owner protection intent depends on perceived sensitivity.	OSNs
Liu and Biczók	System-level analysis; API	Filter logic enforces black/white-lists to block non-consented disclosure.	Smartphone app permissions
Marsch et al.	3x2 randomized experiment	Person-based visual priming increases care for others' privacy.	Smartphone app permissions
Li et al.	Algorithm design	Reputation-based DAG system reduces dishonest data sharing (image-based limitations noted).	Automotive
Pu and Grossklags	Conjoint analysis + SEM	Concern and knowledge influence valuation of own and friends data.	OSNs
Zhang and Zhu	Survey (relational and affective)	Disclosure of others' info driven by social reward and emotional affect.	Privacy Calculus

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Table 1: Existing Research in IDP

Author(s)	Method	Significant Results	IDP Domain
Franz and Benlian [32]	Survey; Mediation analysis	IDP salience nudge makes users 62% less likely to disclose others' data.	Online Social Networks (OSNs)
Amon et al. [34]	Surveys; Perception ratings	Identified IDP clusters (violators, preservers); Sharing likelihood inversely related to privacy.	OSNs
Wirth et al. [35]	SEM on survey	Co-owner protection intent depends on perceived sensitivity.	OSNs
Liu and Biczók [36]	System-level analysis; API	Filter logic enforces black/white-lists to block non-consented disclosure.	Smartphone app permissions

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Pu and Grossklags [38]	Conjoint analysis + SEM	Concern and knowledge influence valuation of own and friends data.	OSNs
Zhang and Zhu [39]	Survey (relational and affective)	Disclosure of others' info driven by social reward and emotional affect.	Privacy Calculus

2.2.5.1. Online Social Networks

IDP research in Online Social Networks (OSNs) primarily examines the dynamics of user disclosure and the factors influencing the protection of co-user data.

- **Disclosure Mechanisms**: Franz and Benlian [32] examined how Instagram users disclose others' personal information, finding that such decisions are serially mediated by responsibility expectations, concern, and salience. They showed that an IDP salience nudge (IPN) reduced disclosure likelihood by 62%, though they recommend exploring multimodal nudge designs.
- **User Modeling and Clusters**: Amon et al. [34] modeled user characteristics influencing IDP perceptions, identifying distinct behavioural clusters—privacy violators, ignorers, and preservers—based on personality traits and engagement patterns. They also found that entertainment value moderated the relationship between privacy perception and sharing likelihood.
- **Sensitivity and Concealment**: Wirth et al. [35] expanded the concept of perceived information sensitivity to explain co-owners' intention to protect others' data. Their model showed that perceived sensitivity and compliance motivation significantly predict concealment behaviours.
- **Valuation and Affect**: Pu and Grossklags [38] offered a foundational model quantifying how users value both their own and others' information, finding that privacy concerns

and knowledge significantly influence valuations. Additionally, Zhang and Zhu [40] explored the role of relationship closeness and affect on Disclosure of Others' Information (DOI) on social media, revealing that DOI is driven by social reward expectations, particularly in intimate relationships, and increased by positive affect.

2.2.5.2. Smartphone Permissions

In the context of dynamic, transactional settings like app permissions, research has focused on enforcement mechanisms and motivational factors.

- **Enforcement Mechanisms**: Liu and Biczók [36] explored the role of relationship closeness and affect in DOI on social media. Results from a 1,007-person sample revealed that DOI is driven by social reward expectations, particularly in intimate relationships. Positive affect also increases DOI likelihood, emphasizing the emotional dimension of IDP behaviours.
- **Prioritization and Priming**: Marsch et al. [37] investigated smartphone app permissions through a 3x2 experimental design. Their findings indicate that users generally prioritize their own privacy over others', especially when permissions are presented in abstract formats. However, person-based visual priming helped mitigate this self-serving bias.

2.2.5.3. Automotive and Location Privacy

Very few studies investigate the impact of IDP risks in automotive contexts, and existing work remains limited in scope.

- **SIoV Data Sharing: Li et al.** [9] proposed a DAG-based reputation mechanism for the Social Internet of Vehicles (SIoV) that deters peer disclosure of sensitive information through external sensors. While effective in promoting 'honest' sharing behaviour, the model currently addresses only unauthorized captures of image-based sensitive data relating to other vehicles, neglecting the spectrum of biometric and physiological data collected inside the cabin.
- **Co-location Privacy:** Other studies, such as Olteanu et al. [21], have touched upon the co-location privacy of vehicles by quantifying IDP risks with location data.

Although the phenomenon is relatively scant in the vehicular domain compared to other domains [40, 34, 35, 32, 9, 37, 39] IDP has been alluded to by several authors, including Ervits and Maintz [41], who examined privacy perceptions surrounding infotainment systems in Intelligent Connected Vehicles (ICVs), focusing on how such systems collect personal data extensively to support entertainment, navigation, and convenience features. Key findings indicate young consumers' willingness to exchange personal data for convenience offered by infotainment services, regardless of explicit warnings about the privacy risks. Although the authors do not discuss IDP explicitly, their results create the conditions under which IDP emerges: Infotainment systems do not only collect data about the consenting user but also about passengers and potentially other road users. Thus, it is plausible that an individual's decision to use a service may induce privacy risks for others potentially without their awareness or consent.

Similarly, Cheng et al. [42] posited that disclosure decisions required to appropriate the benefits of IT-enabled ridesharing services may be influenced not only by perceived (privacy) risks to oneself but also by perceived (privacy) risks to other users based on the principle of the third-person effect. They encouraged research into how these perceptions shape disclosure decisions in shared contexts.

As such, the need for empirical validation of the IDP problem cannot be overstated. Thus, our contributions which align with the objectives of the project, include:

- Validating the first Structural Equation Model (SEM) linking IDP risk to trust and acceptance, specifically for the context of shared SAE L3+ CAVs.
- Providing the first objective, physiological validation of IDP-induced stress in an automotive simulator environment, using HRV and SCR to empirically ground the severity of co-passenger-induced privacy risks.
- Developing a framework for translating IDP human factors into machine-readable formats potentially with the technical specifications required for privacy-aware HMI development.

3. Human Factor Taxonomy for In-Cabin Adaptation

This chapter details the methodology required to model and segment occupants of CAVs. The primary objective is to develop a comprehensive understanding of Human Traits across the user base to inform the design of adaptive, personalised, and inclusive mobility services.

3.1. Human Trait Categories

To foster adaptiveness and personalisation of in-cabin services, we categorize the AutoTRUST user population, comprising both drivers and passengers, into distinct user profile clusters with goal of identifying distinct target groups (personas) and providing machine-readable specifications that enable the vehicle to respond appropriately to different user segments.

Table 2: Human Trait Categories

Trait Category	Characteristics	Data Source/Task	Purpose
Static Traits	Stable, enduring features, including demographic variables, technology familiarity, sensory preferences, etc.	Surveys, Interviews, Focus Group Feedback, etc.	Define stable user profile clusters and inform system baseline configurations.
Dynamic Traits	Context-dependent states, including biometric responses (HRV, SCR, etc), emotional state, cognitive load, etc.	In-Cabin Monitoring, and Physiological Data.	Enable real-time adaptation of services to align with current physiological and psychological state.

These clusters are defined by the convergence of various characteristics, including demographic variables (e.g., age and social status), technology familiarity, and behavioural profiles based on surveys and focus group feedback, and real-time physiological and biometric data (see

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Dynamic Traits	Context-dependent states, including biometric responses (HRV, SCR, etc), emotional state, cognitive load, etc.	In-Cabin Monitoring, and Physiological Data.	Enable real-time adaptation of services to align with current physiological and psychological state.

). The resulting, machine-readable human factors profile is essential for enabling adaptive, personalized, and inclusive in-cabin environments and personalized Virtual Assistant System (VAS).

Related to WP2, we organised an internal workshop to define a sample of personas. After a brief presentation of the project pilot sites the groups then brainstormed technological and design solutions that could support them. This exercise served not only as a creative engagement but also as a method to surface real-world design implications that may not be captured through purely technical analysis.

The workshop resulted in a diverse set of personas, each highlighting unique barriers and opportunities for inclusive design:

Persona 1: Sal – Sensory-sensitive commuter (35)

Sal represents individuals with heightened sensory sensitivity, a profile echoed strongly in several D2.3 focus groups where users described discomfort with loud announcements, abrupt signals, and visually cluttered interfaces. Her static traits include high digital literacy, preference for visually clean environments, and a need for predictable and minimally intrusive notifications. These traits translate into a mobility profile where she relies on subtle haptic cues, configurable visual alerts, and noise-controlled environments. Sal highlights the need for accessible UI modes designed for neurodiverse users or users experiencing sensory overload.

Persona 2: Leo – Daily wheelchair user and student (25)

Leo's persona draws from D2.3 findings with participants with mobility impairments who consistently reported challenges related to boarding, secure anchoring, and spatial constraints. His static traits include the permanent use of a wheelchair, strong familiarity with public transport systems, and preference for clear physical affordances such as reachable buttons, stable handholds, and predictable spatial layouts. His needs illustrate the requirement for low-floor autonomous vehicles, automated ramps, accessible seating configurations, and user interfaces positioned within reach for seated passengers.

Persona 3: Cecilia – Older adult navigating complex urban mobility (62)

This persona reflects the profiles gathered from older adults in the D2.3 focus groups, who frequently described a combination of mild mobility limitations, moderate technological familiarity, and linguistic or cognitive barriers when interacting with digital systems. Cecilia's static traits include age-related sensory changes, increased anxiety in unfamiliar environments, and preference for slow-paced, clearly structured instructions. She underscores the importance of multi-language support, simplified routing information, ergonomic handrails, and gradual communication cues within the autonomous vehicle.

Persona 4: Markus – Blind or visually impaired urban traveller (mid-40s)

Based directly on the insights from the D2.3 focus group with blind and visually impaired participants, Markus represents users whose static traits include complete or partial vision loss and reliance on auditory and tactile modalities. His mobility habits depend on consistent sound cues, tactile feedback, and accessible spatial orientation aids. The persona demonstrates the necessity for spatialized audio guidance, reduction of overlapping sound layers, tactile entry markers, and VAS instructions optimized for screen readers and audio-first interactions.

Persona 5: Elena – Privacy-conscious, tech-literate passenger (28)

While not associated with physical accessibility constraints, Elena's traits reflect another pattern observed in D2.3, particularly in discussions on privacy, technology acceptance, and perceived safety. Her static traits include strong data protection concerns, preference for transparent system behaviour, and familiarity with digital services. She represents users who require explicit consent flows, configurable privacy settings, and explainability features that clarify how and why the system is acting at any given moment.

These personas, grounded in the static traits collected throughout WP2 activities, illustrate the diversity of long-term user characteristics that must be accounted for in the personalisation and inclusiveness strategies of AutoTRUST. They not only summarize key demographic and behavioural patterns but also formalize the stable user dimensions that will inform the system's initial configuration parameters and serve as reference points for dynamic adaptation mechanisms.

3.2. Ethics and Vulnerable User Profiling

The AutoTRUST project adopts a multidisciplinary and human-centered approach to ensure that Connected and Automated Vehicles (CAVs) are designed and validated with a broad spectrum of user needs in mind. The methodological framework for participant involvement is grounded in iterative co-creation cycles, integrating feedback loops from diverse user groups across the four pilot sites. This approach aims to generate continuous insights into user trust, perceived safety, accessibility, and inclusiveness, ultimately supporting the development of resilient and socially sustainable AV models.

To ensure representativeness and inclusivity, the recruitment strategy prioritizes the engagement of participants from heterogeneous backgrounds, including not only technical partners and professional drivers but also individuals from vulnerable or underrepresented groups. These include older adults, persons with reduced mobility, individuals with sensory or cognitive impairments, and caregivers. By doing so, the project acknowledges the ethical imperative of equitable participation in shaping technologies that will impact all citizens. The selection and involvement of participants follow established ethical guidelines and GDPR-compliant data management protocols, ensuring informed consent, privacy, and data protection throughout all stages of the research.

The participatory process is structured around context-sensitive pilot activities. Each pilot implements engagement sessions tailored to its technological and social context: for example, UIA conducted an initial expert workshop to identify ethical and usability challenges, Siemens organised co-creation sessions with users experiencing mobility or sensory restrictions, and CARITAS engaged older and socially vulnerable individuals to understand barriers and expectations towards AV adoption. These early interactions serve as diagnostic inputs for refining user profiling methods and adaptive interface concepts, providing empirical grounding for subsequent design iterations.

Building on this foundation, T1.4 and WP2 continue to coordinate the transversal involvement of participant groups, ensuring that user feedback remains integral to project evolution. The insights derived from these engagement activities will inform the development of user-focused ethical guidelines and inclusive design principles, to be consolidated in future deliverables. This participatory methodology not only strengthens the ethical robustness of the project but also contributes to enhancing public trust, social acceptance, and perceived legitimacy of automated mobility solutions.

4. Mapping to Personalization Triggers

This section details the methodology for mapping identified human traits and conditions to specific in-cabin personalization triggers. These triggers represent the CAV's adaptive mechanisms to meet the occupant's implicit and explicit needs. The mapping process functions as a dynamic logic model, linking each detected human factor to a corresponding adaptive vehicle response [43] [44].

Prior work demonstrates that physiological and affective states such as fatigue [45], motion sickness [46], thermal discomfort [47], or emotional stress [44] can be reliably detected through multimodal sensing and used to inform adaptive systems. Similarly, research on automotive comfort and interior experience highlights the relevance of personalised seating, lighting, noise control, and support features for maintaining wellbeing and acceptance in automated vehicles [48] [49] [50]. In the context of highly automated driving, incorporating these insights into a coherent mapping framework is essential to support user trust and mitigate discomfort associated with reduced involvement in the driving task [43].

The concept positions the vehicle as an adaptive, context-aware environment capable of continuously assessing occupant states through multimodal sensing and integrated user profiles. Such approaches are consistent with existing guidelines for AI-driven personalisation and inclusive HMI design in automated vehicles [51] [45] [43]. Resulting adaptations may involve environmental tuning, interface simplification, accessibility adjustments, or behaviourally relevant modifications such as smoother vehicle dynamics or tailored information delivery. Evidence from studies on interior environments—including dynamic lighting [50], active sound control [49], and support for long-term seating comfort [52] - demonstrates that these adaptations can directly influence comfort and cognitive load. All adaptations remain under explicit user control, with transparency and reversibility embedded in the design to ensure alignment with ethical and inclusive design requirements defined in preceding work packages.

4.1. Trigger Logic and Adaptation Flow

For every element in the human factor taxonomy, we can define a corresponding set of potential triggers. The proposed AutoTRUST framework operates on a continuous loop of sensing, interpreting, and acting [47].

1. **Sensing & Detection (The Input):** The vehicle uses a suite of sensors and data sources to identify a relevant human factor, including biometric and contextual inputs [45].
2. **Interpretation & Mapping (The Logic):** The system maps detected states to appropriate adaptive actions, considering context and priority [43].

3. **Triggered Adaptation (The Output):** The vehicle executes adaptive actions, altering in-cabin experiences such as lighting, temperature, sound, or HMI configuration [50] [43].

4.2. Personalization Framework

Table 3 provides a comprehensive, though not exhaustive, mapping of human factors from the taxonomy to potential personalization triggers.

Table 3: Taxonomy of Potential Personalisation Triggers

Human Factor Category	Specific Trait / State Detected	Potential Sensing Method(s)	Personalisation Trigger (Vehicle Action)	Desired Outcome
Physiological	Motion Sickness Susceptibility	User profile setting, motion sickness detection module	• **Driving Style:** Smoother acceleration/braking. • **HMI:** Display a stable horizon line on screens. • **Environment:** Increase fresh air ventilation; diffuse ginger or peppermint scent.	Mitigate nausea, enhance ride comfort [46].
	Fatigue / Drowsiness	Eye-tracking, yawning detection, visual drowsiness detection, HRV	• **Alerts:** Haptic seat/wheel vibration, auditory chime, Assistant warnings. • **Environment:** Lower cabin temperature, increase blue-spectrum light. • **Media:** Play upbeat music or engaging podcast.	Increase alertness, ensure safety [45].
Psychological / Emotional	Stress / Anxiety	HRV, voice tone, facial expression	•**Guidance:** Offer calming, reassuring voice prompts. •**Environment:** Initiate a guided breathing exercise via audio and ambient light pacing.	Reduce stress and improve trust [50] [49].

Furthermore, to operationalise the human-centered findings with respect to IDP, we provide tentative links from IDP-related human factors to measurable indicators and HMI requirements (Table 4):

Table 4: IDP-Related Personalisation Triggers

Human Factor Category (IDP Sensitivity)	Measurement Method	HMI Requirement
Co-passenger privacy intrusion (e.g., biometric data captured without consent)	HRV changes, SCR peaks, and self-report discomfort	Adaptive notification system that alerts non-consenting passengers about potential IDP breach using preferred communication modality)
Shared CAV Trust Erosion	SEM outputs correlating IDP with trust in shared CAVs	A dashboard/interface that provides transparency, i.e., which sensors are active and for whom (at the appropriate level of granularity)

Thus, the vehicle should provide sensor pipelines that localize sensors to specific seats, filtering out or anonymizing non-consenting individuals' data at the point of capture while offering clear opt-in/opt-out controls.

Building upon the personas defined through WP2 activities, the next step is to translate these user profiles into meaningful personalization triggers signals, behaviours, and contextual cues that the vehicle can detect and respond to. In this framework, each persona embodies an ideal interaction scenario: a representation of how the autonomous vehicle should ideally perceive, interpret, and adapt to individual users. These interaction pathways illustrate how static traits set up initial system expectations, while dynamic traits activate moment-to-moment adjustments to support comfort, safety, trust, and usability. The ideal interaction is therefore not a fixed script, but a fluid and anticipatory relationship between the user and the vehicle, shaped by multimodal sensing, contextual awareness, and explainable decision-making.

For example, in Persona 1, Sal, the ideal interaction begins at the moment she is recognised, either through her device profile or voluntary in-cabin selection. The system automatically configures a low-stimulus environment: the lighting shifts to soft, balanced tones, and auditory notifications are reduced in volume and frequency. When the vehicle needs to communicate, it does so through discreet haptic pulses or simple, uncluttered visual symbols that avoid flashing or overstimulation. If Sal shows signs of sensory fatigue, such as reduced movement, eye strain, or increased fidgeting detected by on-board sensors - the system progressively reduces environmental intensity or offers quiet-mode suggestions through the VAS. The interaction remains unobtrusive and respectful of her preference for minimal intervention, while still ensuring safety and responsiveness.

Across all personas, several categories of personalisation triggers emerge as central:

- **Identity-based triggers** (e.g., recognition of static traits such as disability, sensory preferences, and language).
- **Context-based triggers** (e.g., boarding conditions, crowding level, lighting, noise).
- **State-based triggers** (e.g., stress, motion discomfort, attention patterns).
- **Task-based triggers** (e.g., need to navigate, board, anchor, or transfer).

The ideal interactions for each persona involving such triggers activate adaptive behaviours from the vehicle, ensuring the experience remains accessible, trustworthy, and tailored.

4.3. Ethical and Inclusive Design Considerations

Consistent with our project's ethical framework, all personalization features are explicitly designed to enhance user autonomy and choice. Each adaptive function is opt-in, and under the user control users must give informed consent (as defined under GDPR: freely given, specific, informed) [53] and can adjust or disable adaptations at any time. Clear feedback mechanisms (for example, visual prompts or status reports) keep users aware of any active personalization, supporting transparency, and understanding [54] [55].

In line with EU guidelines for Trustworthy AI, the system prioritises human agency, oversight and explainability so that personalisation never acts as a black box beyond the user’s influence. System architecture also enforces transparency, reversibility, and accountability as core requirements. All data-driven adaptations are explainable (e.g. through easily understandable summaries or visualizations) and can be reverted or adjusted by the user. Such principles mirror the EU ethics requirements for AI systems (transparency, diversity, fairness) [54]. Special attention is given to comfort triggers for older adults and users with reduced mobility: for example, cabin displays and controls will follow ergonomic guidelines (high illumination, large fonts, matte surfaces to reduce glare) that accommodate age-related vision changes [56]. Likewise, audio alerts will use clear, mid-frequency sounds (avoiding very high pitches) and allow volume adjustment. These accommodations reflect universal design principles of interfaces that are simple, flexible, and perceivable by people of all abilities [56] [53] [52] [48]. In summary, the personalization system will be ethically grounded: it gives each user clear choice and control, maintains full transparency, and includes safeguards (e.g. easy undo options) to ensure trust and inclusivity from the start [51].

4.4. Expected Outcomes

This subsection outlines the tangible outputs of WP4, translating human-factor insights into adaptive personalization tools. Building on the taxonomy, behavioural cues, and privacy considerations, the expected outcomes are:

- **Adaptive Feature and Trigger Catalogue**: Mapping personalization capabilities to sensor-detected conditions and user states.
- **Integration Guidelines:** Linking human factors models with sensor and inference modules for principled adaptation.
- **Adaptation of Logic Prototypes**: Software prototypes tested in lab and pilot vehicles to validate real-time personalization.
- **Design Recommendations:** Guidelines for transparent, inclusive, and user-controlled adaptations.

Together, these outcomes operationalise personalization as ethically grounded, data-driven adaptations, ensuring CAVs evolve into responsive, human-centered environments that enhance comfort, inclusiveness, and trust.

4.5. Adaptive Feature and Trigger Catalogue

A comprehensive catalogue of personalization capabilities linked to triggering conditions. The project will enumerate adaptive features (e.g. seat and climate adjustments, driving style modes, infotainment preferences) and specify the sensor-detected triggers or user states that activate them. Each feature will be mapped to user profiles or states identified in the human factors taxonomy (e.g. driver fatigue inferred from slow eye-blink rate), so that if a condition occurs, the appropriate adaptation is applied.

4.6. Integration Guidelines

We will produce technical guidelines linking human factors taxonomy (WP2) with sensor and inference modules (WP3). For example, the guidelines may specify that a sustained elevated heart rate combined with agitated gestures (detected via wearable and cabin sensors) indicates stress, triggering the calm mode of adaptation. These guidelines will enable developers to connect user models with real data streams in a principled way.

4.7. Adaptation of Logic Prototypes

Working software prototypes implementing the above logic will be built and tested. These prototypes (to be deployed in labs or pilot vehicles) will apply the catalogue s triggers in real time, adjusting the cabin environment (lighting, temperature, seat support, alert modalities, etc.) to user needs. Pilot trials will collect user feedback and measure effects on comfort and trust. Prior research shows that adaptive personalization in AVs can significantly improve passenger comfort and trust [56] [55].

4.8. Design Recommendations

Based on prototyping and evaluation, we will deliver guidelines to ensure transparency, inclusivity, and user control in adaptive vehicles. This includes best practices for consent interfaces, user feedback displays, and accessibility of accommodations. The recommendations will explicitly address fairness and bias avoidance (following AI requirements for diversity and non-discrimination [55]) and describe how to build user trust (for example, by providing clear, multimodal explanations of any adaptation). By operationalizing personalization as a set of ethically grounded, data-driven adaptations, the project transforms CAVs from passive transport into responsive, human-centered environments. For example, frameworks like Persona-PhysioSync AV have shown that personalizing the vehicle experience based on passenger traits and physiological state can substantially enhance trust and comfort [56]. Similarly, providing clear multimodal feedback in AVs has been shown to significantly increase user trust [55]. Focusing on inclusive, transparent design, our work will promote passenger comfort and wellbeing – effectively creating CAVs that adapt to and support each user [50] [47] [46].

5. Conclusion

This deliverable establishes the human-factor foundations necessary for the development of adaptive in-cabin services within AutoTRUST. By synthesising insights from WP2, behavioural research, and the broader CAV literature, we define a structured Human Factors taxonomy that operationalises user traits, dynamic states, contextual conditions, and shared-cabin considerations such as interdependent privacy.

The resulting taxonomy supports the construction of representative personas and provides the basis for a set of clearly defined personalisation triggers. Together, these outputs enable systematic translation of user characteristics and behavioural cues into actionable in-cabin adaptations. This ensures that forthcoming system development aligns with user expectations, accessibility needs, and safety-critical behavioural patterns.

The work presented here directly informs the next steps in WP4, particularly the implementation of adaptive modules, multimodal sensing integration, and the technical validation of in-cabin personalisation strategies. Future deliverables will build on this foundation by operationalising the taxonomy into machine-readable formats, implementing real-time inference pipelines, and validating adaptations with users across diverse demographic and situational profiles. This deliverable therefore acts as a key enabler for achieving AutoTRUST's vision of safe, inclusive, and trustworthy automated mobility.

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