GenAI-Driven Adaptation in Next-Generation Automotive Human–Machine Interaction

Nareddy Abhireddy
Independent Researcher
nareddy.abhireddy.researcher@gmail.com

Abstract

The rapid improvement of interactive generative artificial intelligence systems, such as ChatGPT and DALL·E, enables ample opportunities for generative AI applications in various fields. In the context of the automotive domain, their utilization is expected to provide personalized in-vehicle experiences and services, as well as behavior-adaptive interfaces for both drivers and passengers. Recent advances in natural language processing and image synthesis open new horizons for addressing the technical challenges of enabling personalized infotainment experiences and behavior-adaptive multimodal interfaces in vehicles. Infotainment systems can benefit from their user intent modeling ability to deliver contextually relevant responses, while the rich generative models trained on large-scale visual datasets can enhance communication of driving states and intentions. Inferring drivers' emotional states from physiological signals enables the incorporation of multimodal signals into the design of intuitive interfaces that adapt to user behavior, situational context, and mental stress.

Generative AI for Personalized In-Vehicle Experiences and Behavior-Adaptive Interfaces: adopt an objective, evidence-based scholarly tone; present clear, formal arguments with structured progression and well-supported claims. Research design is delineated within a dedicated sub-section. The discussion covers user intent representation and preference modeling, design principles for behavior-adaptive interfaces, and multimodal interaction in automotive environments. Data acquisition, privacy, and ethical aspects receive attention. Data acquisition, security, and consent are addressed alongside fairness, transparency, and accountability considerations. System architecture is examined in terms of among on-device versus cloud-enabled personalization, real-time inference and latency constraints, and safety-critical integration. Evaluation encompasses user-centric methodologies, objective metrics for adaptivity and usability, and simulation and field trials. Finally, deployment scenarios and applications are explored, focusing on infotainment personalization, driver state and stress monitoring, and route and context-aware adaptation.

Keywords : Generative AI, personalization, behavior-adaptive interfaces, automotive HCI, multimodal interfaces,In-vehicle personalization,Driver behavior modeling,Adaptive human–machine interface (HMI),Context-aware interaction,Multimodal user sensing,Generative conversational assistant,Real-time intent prediction,Emotion-aware UX,Proactive recommendations (in-car),Privacy-preserving personalization.

1. Introduction

Automotive technology has evolved rapidly and shows no sign of slowing down. Current trend highlights include advanced driver-assistance systems, but these often fail to meet user needs and preferences. Upcoming generations of vehicles are more amenable to personalization than ever, offering opportunities to enhance the driving experience. Vehicles automatically adapted to users' preferences and behaviors would ultimately increase safety and satisfaction through recommendations and automated adjustments. Generative artificial intelligence (GAI) provides novel, flexible tools capable of developing tailored services when

explicitly trained for personalization. Comprehensive consideration of the unique challenges present in automotive scenarios can ground the design of Generative-AI approaches for vehicle-user personalization. Such considerations encompass the identification of user intent; modeling of stable, yet evolving, preferences; principles for behavior-adaptive interfaces; support for multimodal interaction; data acquisition, usage, and security; requirements for on-device versus cloud-enabled computations; latency constraints; and integration with safety-critical systems.

The proximate goal of this work is therefore to establish the theoretical foundations for future Generative-AI developments that specifically target personalization of in-vehicle experience; create adaption-relevant models of road-user state and behavior; use these to specify a personality for GAI systems that can autonomously adapt in-vih0chicle infotainment systems; enable the design of behavior-adaptive interaction techniques; and address the privacy and ethical implications of acquiring the data required to reain such models. Of particular interest is how such developments can contribute to the generation of a more responsive in-vehicle experience by supporting intelligent GAI systems capable of adapting their personalities to, for example, the driver's current state or stress level; adjusting in-car recommendations based on the emotional impact of proposed music or podcast selections; and executing context-aware modifications during road travels through timely changes in route and behavior.

1.1. Background and Significance

Colloquial and natural conversation with artificial intelligence (AI) systems is drawing great interest owing primarily to the advent of generative AI. Applications based on generative AI have opened new avenues in the Infotainment and Service domain of Intelligent Vehicles. Generation of personalized interactions that embody the driver's actual context and state is a logical continuation of the generative AI paradigm. Maturity of large language models (LLMs) has introduced state-of-the-art capabilities for natural language understanding and generation. Interfacing with a navigation system in natural language by asking questions instead of navigating through multiple screens is a step towards personalized naturalistic interactions in infotainment systems.

While knowledge from LLMs can be leveraged to deliver enriched content, easy access to the knowledge and learning from the driver's context and preferences will take conversations with the system to the next level. Understanding the driver's real-time state and mood offers a potential way of making recommendations that have an impact as it truly understands the driver in that moment. Thus, a generative AI system that adapts to the inferring driver context and preferences and delivers a system that understands and takes on the personality of the driver by adapting contents as per the driver's mood and contextual situation becomes possible.

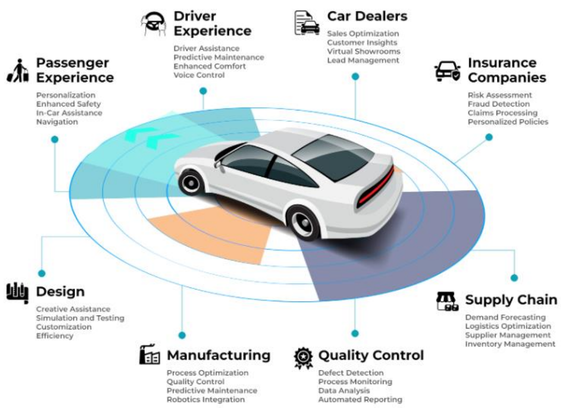


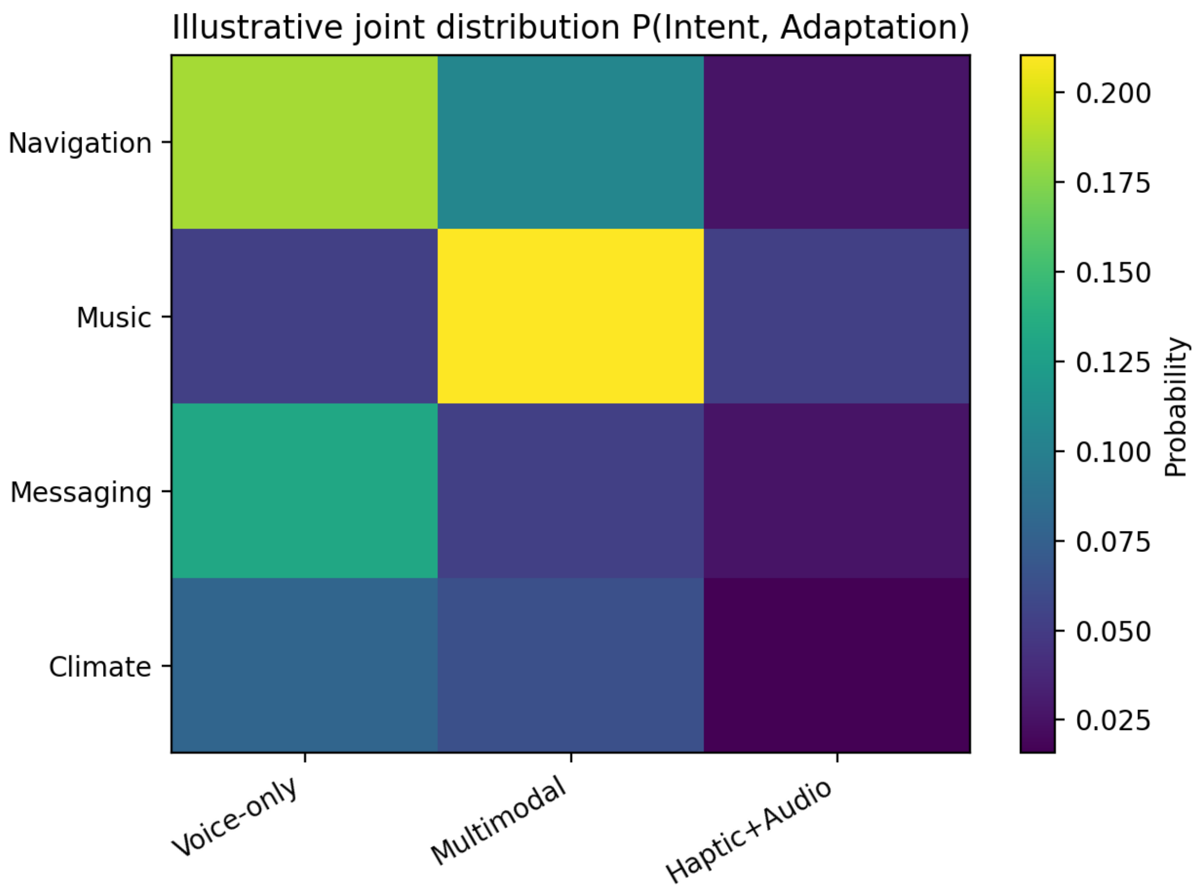
Fig 1: Generative AI for Personalized In-Vehicle Experiences

2. Theoretical Foundations of Personalization in Vehicular Contexts

The design and deployment of user-centric systems around a personalized automotive experience, focusing on virtual and augmented reality interfaces, interaction modalities, user intent and preference modeling for the infotainment system, and integration of generative artificial intelligence models for the automotive ecosystem.

Recognition of the importance of personalization in improving user experience has led to the development of behavior-adaptive interfaces in many application domains. However, all these personalization efforts suffer from the lack of a definitive model for user intent, contexts, and long-term preferences. Recent research in generative artificial intelligence has enabled complex tasks like realistic image generation, media creation, and text generation that are traditionally difficult like composing original music. The user-centered approach recognized in these generative tasks opens up exciting opportunities for personalized or context-aware applications as well as behavior-adaptive interfaces in the automotive domain.

Personalization aspects of user-centered systems for augmented and virtual reality-based infotainment and user-adaptive control interfaces are detailed first. User intent modeling, long-term user preference modeling, and multimodal interaction modeling in a vehicular context are then considered. Finally, related research directions beyond virtual and augmented reality systems but focusing on user-centered personalization are explored, including stress detection in driver behavior and personalized route recommendation.



2.1. Research design

Personalization in vehicular contexts is investigated by combining user intent representation, preference modeling, and behavior-adaptive interface design principles within the context of generative AI, thereby establishing a foundation for enabling context-sensitive and multimodal interaction in vehicles. Personalization enables vehicular systems to go beyond mere detection of physical movements or intents by constituting a form of customization capability that adapts to the user's predispositions, preferences, attitudes, and/or expectations. The interaction modalities generally supported by multimodal vehicular systems (e.g., vehicular infotainment systems) can also be enhanced to provide a behavior-adaptive capability through the personalization of the detected intent.

Such multimodal interaction augmentation has traditionally relied on machine learning or heuristic rule-based approaches and is heightening interest because generative AI is poised to become the next frontier in artificial intelligence. Designing dedicated

models that exploit user behavior to enhance the personalization and adaptiveness of interfaces and experiences is a logical extension. Such developments will complement existing research approaches, broadening the exploration of user intent into a more general interaction across the full spectrum of personalization in vehicular contexts.

Equation 1: Likert acceptability rule (mean rating + threshold)

Step-by-step derivation

Let a generated content sample receive ratings:

$$r_1, r_2, \ldots, r_n \text{with} r_i \in \{1,2,3,4,5\}$$

Step 1 (mean):

$$r_{\text{mean}} = \frac{1}{n}\sum_{i=1}^{n} r_i$$

Step 2 (acceptability decision): with threshold $\tau = 3.5$,

$$\text{Accept} = \begin{cases} 1 & \text{if } r_{\text{mean}} \geq \tau \\ 0 & \text{otherwise} \end{cases}$$

3. Generative AI Models for In-Vehicle Personalization

Generative AI offers a natural and promising catalyst for in-vehicle personalization, enabling models to comprehend users' aversions and enthusiasms through the lenses of intention, tastes, and context, accordingly tailoring diverse system factions. The utilization of generative AI entails several fundamental and functional components. User intention modeling enables ongoing tracking of users' immediate aims (exercise versus recreation) for specific frames to inform and tune path experiences, interface tempo and visual structure, journey suggestions, and even vehicle settings. User preference representations of long-term preferences across all senses suitable for the current journey context may be represented, queried, and coupled with multimodal adaptation principles to facilitate the adaptation of any in-vehicle digital product. The synthesized guidance combined with route attributes accommodates the generation of location-aware procedures, thereby enabling immersion in altruism, cultural engagement, and local sources of delight or challenge in spatial surroundings.

Intuitive Vehicle Speech Interaction, Methodical Drivers-Only Speech Interaction During Traffic Challenges, and a Toy-Set Approach to Drivers-Only API Design form transparency and policy modeling structure. User sentiment about multimodal interaction, joint visual-procedural interaction, and increasing adoption of vehicle dialogue substantiates the exploration of any adaptive manner of response via security routers. Guidelines for Generative AI Systems Texture Frameworks capable of enabling trade-off, appropriateness, and intimacy are expected to lead to a road-map and deliver adaptive guidance compatible with expressive audiovisual synthetic-character templates.

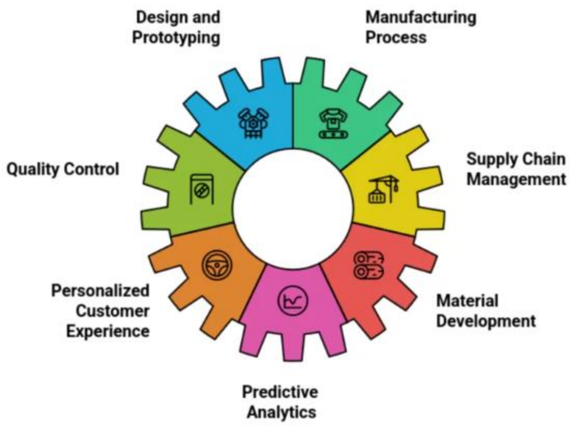


Fig 2: Generative AI in Automotive

3.1. User Intent Representation and Preference Modeling

User intents for personalization in an in-vehicle context can be represented by multi-task learning models capable of estimating environment-adaptive preferences across multiple applications and enabling one-shot personalization. A new framework generates high-fidelity user-aware behaviors for complex entertainment profiles, combining a probabilistic preference model, generative reinforcement learning, and a heterogeneous portfolio of latent variable-based generative networks. A proof of concept validates on-the-fly generation of user-specific infotainment recommendations by leveraging users' background, moods, and listening behavior.

Reliable representation of a driver's current journey-based intent and context offers great potential for personalized automation of in-vehicle interface services. Contextual information can be exploited for personalized in-vehicle systems, such as driver state recognition using visual information for state-dependent stress adjustment, steering behavior for accelerating user-aware agent control, style session personalization for multimodal agent systems, and parameter optimization for context-sensitive human-vehicle-interaction optimization. User-centric one-shot personalization models allow real-time adjustment of visual content to user background or eliciting mood.

3.2. Behavior-Adaptive Interface Design Principles Human-vehicle interaction should be designed to detect and adapt to variations in drivers' physical and emotional states. Incorporating AI models that control in-vehicle systems according to human behavioral intent enhances system effectiveness and user experience. A behavior-adaptive interface (BAI) predicts implicit user intent via driver observations and modulates interface characteristics and operations to facilitate user-system interaction. Core design principles involve analyzing drivers' facial expressions and pupil dilation, model training, and system activation. Sensor data provides insights into users' emotional states, attention levels, and driving states; these modulations contribute to an engaging user experience, particularly during non-driving phases.

BAIs bridge human expectation and system capability; they detect user intent and modulate controllable system attributes in real time. Such detection requires modeling users' facial expressions, gaze direction, and physiological status. Modeling aims to map observations to user intent and assess its potential to enhance experience and reduce workload. Model performance quantifies the system's applicability range. Kinematic data during driving and non-driving phases establish state duration thresholds; adaptive regulation improves experience in non-driving intervals and creates a sense of story consistency.

3.3. Multimodal Interaction in Automotive Environments

In-vehicle interaction heavily relies on visual or tactile modalities by default. In this case, Generative AI-enhanced multimodal interaction design principles are proposed to maximize user experience both from usability and adaptivity perspectives, facilitating the adoption of multimodal interaction naturally and seamlessly. The techniques enable automatic generation and adaption of images (e.g., icons, background, etc.), sounds (e.g., alerts, notifications, etc.), and vibrations (haptics) for implementing a personalized user experience in various aspects, such as visual UI, auditory cues, and vibrotactile feedback based on the situational context (e.g., routing, driver state, environment) and user preference and condition (e.g., preference group, stress level).

Choosing a non-dominant modality for information presentation can be helpful either in avoiding information overload or in enhancing the safety by providing an appropriate warning or notification in a non-visual form. However, it is challenging for the users to spontaneously switch from visually-centered interaction to a multimodal interaction in an effortless and efficient manner. Generative AI techniques can facilitate the process by introducing multimodality to user interaction naturally without users' explicit awareness through adaptively selecting a non-dominant modality for information presentation and by making information decoding more intuitive via establishing a natural association of information content across different modalities through different modality signals (e.g., auditory cues and vibrotactile feedback) that indicate the same information content.

4. Data, Privacy, and Ethical Considerations

Data acquisition and usage for personalization involves several aspects. First, devices require user-specific data to generate personalized experiences. Second, for personalization to be effective, privacy and security must be ensured. To this end, data representing user preferences and interests should be collected, analyzed, and stored in a safe manner, and any possible data leaks should be mitigated. Third, bias toward certain user groups can lead to unfair personalization results; hence, transparency in the underlying machine learning models is essential.

Intelligent agents for personalization systems typically require access to a wealth of sensitive user data. Consequently, it is vital for such systems to provide suitable guarantees on the security of acquisition and storage. It is also important that users' access to certain data remains granular. For example, minimizing the agent's access to a personalized model of user interactions prevents data leaks that affect real users. Furthermore, a legitimate process for data usage must be adhered to, so that ethical concerns arising from unfair personalization results are mitigated.

Equation 2: Entropy-based adaptivity using a joint distribution

Let:

- I= random variable for *user intent*
- A= random variable for *adaptation outcome/decision*
- $p(i,a)$= joint distribution.

Step 1 (marginals):

$$p(i) = \sum_a p(i,a), p(a) = \sum_i p(i,a)$$

Step 2 (joint entropy):

$$H(I,A) = -\sum_i \sum_a p(i,a) \log_2 p(i,a)$$

Step 3 (marginal entropies):

$$H(I) = -\sum_i p(i) \log_2 p(i), H(A) = -\sum_a p(a) \log_2 p(a)$$

Step 4 (one common "match" score): mutual information

$$I(I;A) = H(I) + H(A) - H(I,A$$

4.1. Data Acquisition, Security, and Consent

The collection and usage of personalization-related data in automotive environments raise significant concerns related to confidentiality and security. Addressing these concerns is critical to ensuring the proper adoption of personalized applications in vehicles. From a data-acquisition perspective, it is crucial to guarantee the confidentiality of the gathered information. Therefore, data should only be shared when strictly necessary and only with the user's approval. Such precautions help minimize the leakage of sensitive information.

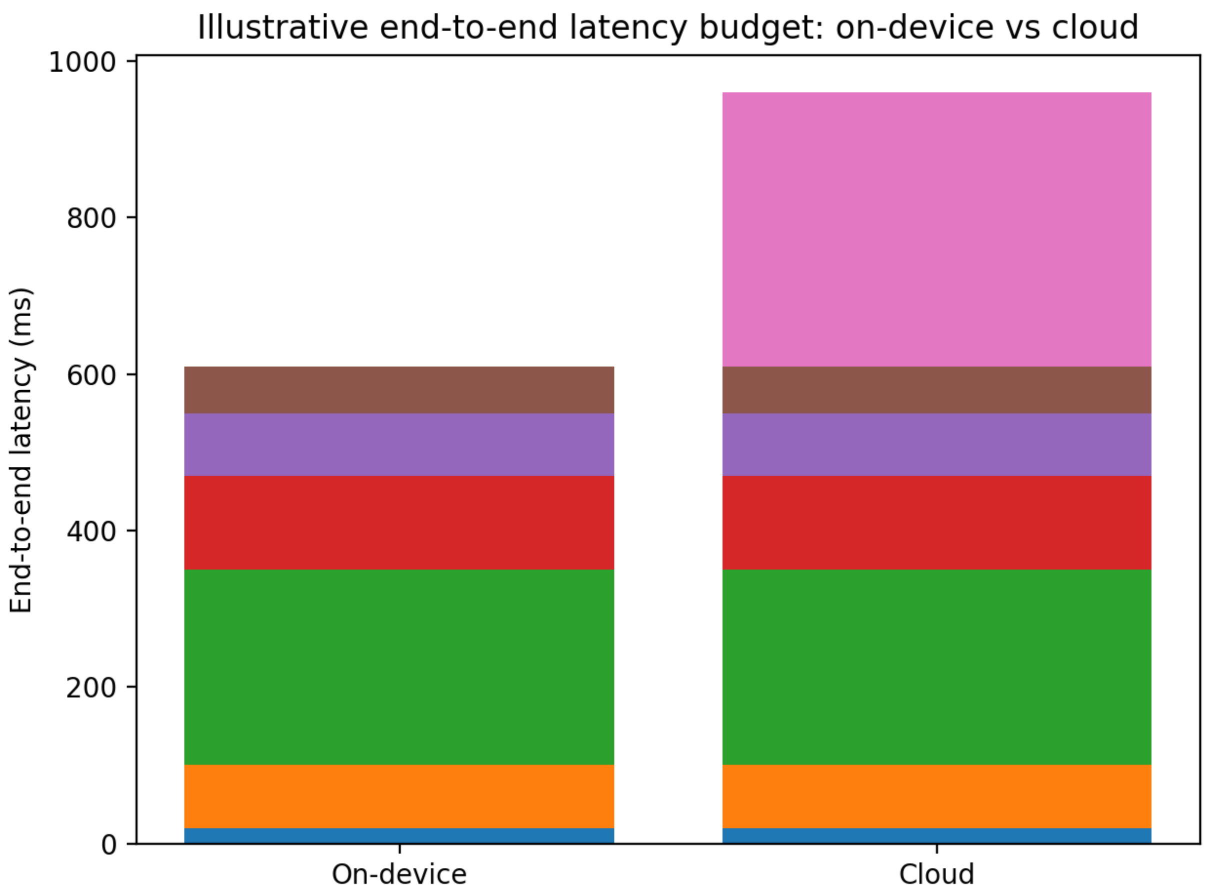
The stored data must also be protected against unauthorized access. Based on the defined usage policy, personal data should be stored on-board the vehicle whenever possible. Such an approach helps contain the accrued data footprint and avoid privacy breaches in the event of a cloud server data leak. In situations in which the adaptation relies on behavioral or contextual data that cannot or should not be collected on-board, a two-step anonymization process is proposed: first, sensitive information is filtered out of the data stream before sending it to the cloud for inference; next, the response is anonymized before being relayed back to the user. Although user consent is always required for the cloud inference to take place, adopting this strategy helps minimize the risk associated with sharing the data. Transparency is also key in this aspect. To ensure that users are aware of how their data are

employed and are able to manage them effectively, an explicit dashboard can be implemented, enabling users to handle their consent and change the usage policies.

4.2. Fairness, Transparency, and Accountability

Fairness, Transparency, and Accountability. The critical role and influence of AI systems in daily life has necessitated and rekindled interest in the field of AI ethics, which includes the notions of fairness, transparency, and accountability. There are no definitive solutions to these challenges, particularly with respect to fair systems and procedures in context-aware personalization. Various biased behaviors, data, and algorithms in recent AI systems have led to serious and, in some Worsen deaths. Frameworks that encompass a wide range of fairness definitions, metrics, and characterization techniques are still susceptible to those biases and require a research focus on fairness theories and definitions in a problem-specific context.

Generative AI approaches for personalizing infotainment services, assisting with route guidance, and adapting to user states should comply with the principles of fairness, transparency, and accountability. It is crucial to support fair access to devices, systems, or services for all users, regardless of their characteristics; user data, models, services, and message generation must remain free of bias and discrimination during the generation process; and user data privacy must never be compromised. Periodic model and data snapshots, as well as a thorough model description, cement transparency. Personalization is further rendered accountable through an ethical data-collection process in which volunteer users are informed that their data will be used for modeling personalized behavior and evaluation, and that these models might adapt to user states or stress.



5. System Architecture for In-Vehicle Personalization

To enable AI-based personalization for in-vehicle experiences and interfaces, a holistic architecture has been designed. It integrates user intent representation, user preferences, and behavior-adaptive display designs. Novel multimodal generative models that rely on user behavior history and contextual cues for multimodal intent estimation support the suggested system. These models are intended for infotainment personalization, adaptive user interfaces, and the design of AI-powered digital co-drivers that react to drivers' mental states in real time.

Personalization can be implemented on-edge or on the cloud, with trade-offs in terms of privacy, data security, and latency. On-edge operation preserves privacy, but changes to models or user preference files require OTA updates. Cloud deployment collects

data for personalized models, ensuring that different car models benefit from the same data pool. Critical safety applications—such as driver state monitoring and alerts—demand low latency and hence an on-device option. With such a modular architecture, different applications can be serviced through appropriate design choices. Data acquisition should be backed by security and consent mechanisms.

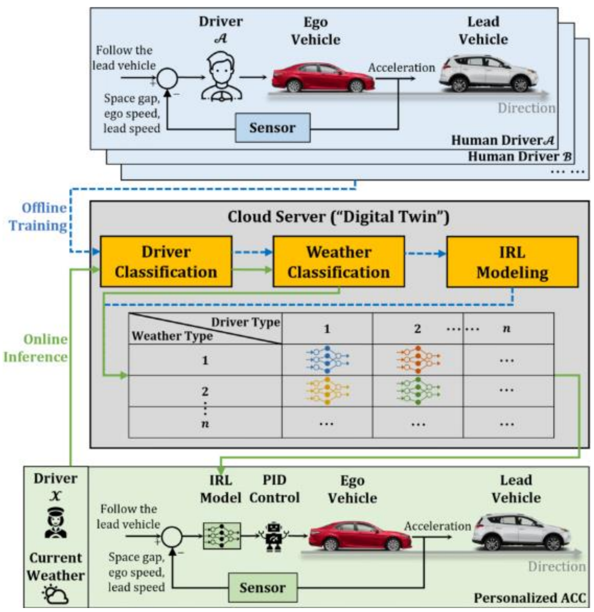


Fig 3: System architecture of the proposed personalized

5.1. On-Device versus Cloud-Enabled Personalization

Four differentiating aspects shape the architecture for in-vehicle personalization systems. First, driving requires mental and motion capacities, limiting users' interactions with entertainment interfaces. Second, vehicle operation is safety-critical. Failures such as delayed responses or incorrect visual representations in augmented-reality head-ups must be avoided. Third, user intent changes rapidly as driving conditions evolve. Therefore, systems cannot rely on a cloud-enabled architecture that requires a round-trip internet connection. Furthermore, the acquisition of private data such as communication history, trip plans, and state-of-mind variations raises privacy issues. User preferences, history, or profile data cannot be stored in a private cloud because drivers and riders change frequently. Safety considerations also exclude the option of large-scale data upload to a cloud-based model with tunable hyperparameters.

These four aspects favor an on-device personalization architecture that uses local preferences and intent. A behavior-adaptive infotainment interface explores drivers' multidimensional behaviors and corresponding multimedia preferences. A learning-based expressive interface personalization for the driver leverages deep learning to optimize a voice assistant in real time as the driver adapts to the road-driving environment. A framework for a context-adaptive life-decision-support system combines the driving

context, user-state-monitoring variables, and user-assistant communication behavior to adapt non-accidental assistance. Traffic incidents are detected through continuous monitoring of the driving context.

5.2. Real-Time Inference and Latency Constraints

The time constraints imposed by human behavior necessitate the fulfillment of latency requirements, which differ across components, interfacing modalities, and application domains. User intent perception must approach a latency of zero, enabling continuous monitoring and allowing the user experience to flow unbroken into the digital environment. To achieve minimal inference latency in user intent recognition, a two-step approach applies Human Activity Recognition (HAR) pipelines, pretrained using large-scale datasets and running in real time on open-source platforms, and custom models that, although having not been pretrained in HAR, are highly optimized. Following detect-and-act paradigms, user action recognition is executed in few-hundreds-milliseconds timeframes, amply satisfying the requirements of most applications and user behaviors. Specialized HAR pipelines fed by fast sensors enable recognition of driver-stress levels as well as driving mode and style, which can subsequently activate and select multiple in-car systems seconds or tens of seconds ahead of user interaction, thus preventing user experience degradation. Several activation variables complement other application configurations, with the related latency imposed mainly on digital-human interactions such as voice generation, visual rendering, and haptic feedback, which—ranging from several hundreds of milliseconds to few seconds—adequately respond to the underlying application requirements.

5.3. Safety-Critical Integration

Safety considerations become paramount when integrating behavior-adaptive interfaces into the vehicle environment. Many of the sensing modalities employed by the personalization framework can help monitor driver fatigue (e.g., facial expression analysis) and the driver's mental workload (e.g., gaze direction). Systems and interfaces for in-vehicle applications operating in fatigued or high-workload settings require careful management to avoid unwanted, dangerous, or misleading adaptation. Audio-based applications, for instance, pose a high risk when paired with high workload or fatigued drivers, likely warranting a static design. Conversely, a multimodal gesture-control application may be a prudent design choice in a high-workload situation because it is perceived as low workload. Designing applications for these four situational parameters—fatigue level and mental workload of the user and types of adaptation being performed (exemplary vs. haptic)—should therefore consider that some combinations of the parameters lead to higher risk than others. Any set of applications with certain parameters likely worthy of extra caution should be flagged for particular attention prior to any in-field deployment.

6. Evaluation Methodologies

Evaluation methodologies encompass user-centric evaluations that gather user feedback and acceptability ratings, combined with objective metrics that measure adaptivity and usability over a broader set of interactions, as well as simulation and field trials that evaluate the technology in real-world driving conditions. The evaluation of personalization-related technologies is challenging due to the variety of characteristics that can be affected by personalization effects and the possible conflicting effects of personalization. For example, offering personalized content is generally preferred by users, but it may also increase cognitive overhead if users must selectively filter the information they receive.

6.1. User-Centric Evaluation

Early-stage evaluations typically use short presentations that span only a few minutes, resulting in a small number of user interactions. In such scenarios, user-centric methods that ensure the personalized options are preferred to the alternatives (for example, as in A/B testing) often cannot be deployed due to the lack of a control group to compare against. Instead, the evaluation focuses on overall acceptability for personalization, and on the fit of the specific content toward profile-based users. Acceptability of generated content is sampled from human annotators who rate each content instance on a 1–5 Likert scale. The samples are provided to annotators in random order to reduce bias related to tiring effects. In addition, the ratings are then summarized by computing mean. To maintain a minimum overall quality level, only samples that receive an average rating ≥3.5 are considered acceptable.

Equation 3: Latency budgeting equations for real-time inference

A common way to express that is a **weighted utility**:

$$U = w_P \cdot P - w_L \cdot L - w_R \cdot R + w_A \cdot A$$

Where:

- P: privacy/security score (higher is better)
- L: latency (lower is better)
- R: risk (safety/privacy failure risk)
- A: adaptivity/accuracy benefit from pooled data

$w_{\backslash *}$: weights based on application criticality

6.1. User-Centric Evaluation

User-centric evaluation approaches enable observations from the perspectives of individual users interacting with the interface. As all users have their unique behavioral traits, experiences, and preferences, user-centric approaches provide a fine-grained evaluation of the user experience. In user-centric evaluations, the user's behavior pattern is recorded and compared against other historical records for the same traffic scenario. The confidence score of the model with respect to the adaptation in a specific interaction is taken into account for evaluation. A confidence score greater than 0.6 signifies that adaptation took place and is favorable for the user. User-centric evaluation measures, therefore, can indicate whether the adaptation took place successfully for the particular user or was ineffective under the given traffic situation.

The lack of a forward model for the adaptation is a critical factor underlying inefficacy. If the interface adapts without consideration of its effect on the user, these adaptations can lead to performance deficits. Hence, the user-centric measure ensures that the interface adapts according to the user's preferences and does not deviate from that prescriptive pattern. In addition to user satisfaction, multidimensional interpretability can be imparted by adding coherence as one of the criteria. The coherence measure indicates how the independent component can be aligned to the preference contingent upon user's mental state. An effective user-specific adaptation technique has lower coherence.

6.2. Objective Metrics for Adaptivity and Usability

User-centered evaluation methods quantitatively measure personalization of the in-car infotainment interface, providing adaptation metrics for the model-to-purpose match with user intents via entropy-based joint distribution. Driving stress levels serve as an objective input to control system adaptability and can be acquired in-simulation or via dedicated sensors in real-world scenarios (e.g., gaze tracking). Quantified adaptivity of generative techniques complements subjective assessments of usability, enhancing the usage experience. In-vehicle modeling addresses enhancement of personalization in vehicular contexts, with emphasis on concepts that go beyond static user preference data. ERD and P300 brain-computer interface activity measure user workload in contrast conditions that shape generative auxiliary response. For safety-critical applications such as pilot-dependent interface design, it remains crucial to build the generative model in a non-intrusive way that not only exploits workload states but also minimizes system invasiveness by emulating stimulus-response relationships. In simulation, P300 attention responses to dVPre, a real-world mind-driven vehicle-piloted infotainment prototype, are acquired by adapted BCI technology that uses superimposed infrared LEDs with inverse canonical sign M-sequences. Driving simulation on the dVPre platform aims at self-driven responsiveness control primarily through vigilance and workload adaptation of a novel mind-system response-assisting driving interface.

6.3. Simulation and Field Trials

To enhance the evaluation of personalization and adaptive vehicle systems, simulation environments for real-world field trials offer time and cost efficiencies. Built on existing simulation frameworks—such as SUMO for traffic simulation and OpenAI Gym for reinforcement learning—unique traffic drop routes and diverse user demographic training datasets can be quickly assembled to demonstrate the concept. For major field trials, a test vehicle collects user data while performing various road tasks; this information forms the basis for model and heuristic training. Models are assessed on the data subset with consideration of model complexity, and behavior-adaptive demo features are deployed within the real vehicle occupant in-vehicle infotainment system.

An additional demonstration environment evaluates adaptivity and usability. The combined framework is extended to enable multimodal realistic visual stimuli, incorporating Unity-based 3D simulation or game worlds, and is benchmarked within an actual GUI-based native application by numerous users. User evaluations test the concept of supporting multiple fare modes through the provision of local fares combined with either an estimated or advanced search mode. Road tolls are calculated using simulations of simulated road systems and either predefined or sugared combinations of A.B-C - and A-B-C fares modeled from real fares for Use case 2.

7. Deployment Scenarios and Applications

Personalization can enhance users' in-vehicle engagement by adapting infotainment applications to situational contexts. It can also support users' mental well-being by providing state-aware recommendations, as well as by monitoring levels of stress via speech, pose, or physiological signals. The proposed adaptive interfaces can be deployed in the vehicle cloud infrastructure, and they leverage a combination of enter and backdoor sensors to listen to the driver's intent and recognize backseat passengers' specific demands.

Infotainment systems can be configured for adaptivity in terms of individual drivers, as well as for active passengers in the back row. When the driver is recognized as the main actor, the interface prioritizes driver-centric information, such as navigation prompts, and minimizes irrelevant streaming content. By contrast, backseat passengers' requests can be processed by dedicated virtual assistants capable of managing multiple intents simultaneously. For both roles, the system considers route characteristics and places of interest along the journey while allowing a relief mode in case of prolonged stress detection.

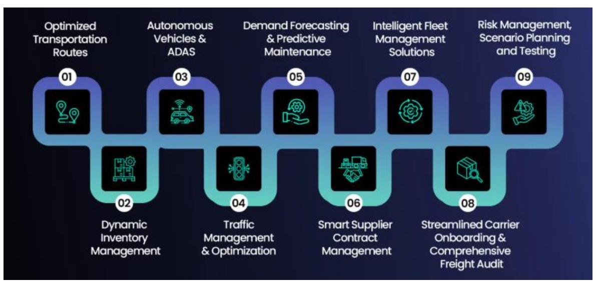


Fig 4: Deployment Scenarios and Applications

7.1. Infotainment Personalization

The infotainment system is among the major interfaces with which a user interacts during their journey in the vehicle and serves as a central hub to mediate communication between the user and other in-vehicle services. Voice is the dominant interaction modality, enabling personal assistants to recognize user intents and respond appropriately. Generative AI-powered chatbots provide a seamless conversational interaction experience. However, even with multimodal interaction, the user experience can still be suboptimal, as state-of-the-art assistants do not understand user personalities and socioemotional conditions. Thus, personalization is an important aspect when adapting the functionality of infotaintment systems.

In this context, personalization focuses on representing user intents and mental states, including socioemotional behaviour and preferences, and combining this information in the design of a behaviour-adaptive interface. Recent efforts have proposed a multimodal persona that continuously tracks the user's personality traits along the Big Five model and then generates context-aware and behaviour-adaptive responses. Hence, the conceived multimodal persona is a suitable candidate for performing personalization within in-vehicle infotainment systems, both as a module focusing on user preferences of diverse dimensions and as an underlying representation of user intents.

7.2. Driver State and Stress Monitoring

Driver state monitoring detection systems based on the analysis of physiological signals play an essential role in road safety, as stressed or drowsy drivers receive critical alerts preceding accidents. However, these monitoring systems must not harm the driver's experience. By using generative AI, both the user's experience and the detection performance can be improved simultaneously. Specifically, the driver's heart rate variability (HRV)—which reflects stress and fatigue levels—can be inferred by modeling the mapping between HRV and driving data.

In addition, a system that modifies the possibility of accurate HRV inference in real time is defined through on-device AI. A reduced HRV detection can lead to an increase in acoustic stimulation and suggests that drowsiness is a possible reason behind the reduced HRV. By preventing a harm to the driver experience while maximizing the accuracy of HRV-stress detection, these results show that generative AI is able to support safety in automotive systems.

7.3. Route and Context-Aware Adaptation

Route and context-aware adaptation extends personalization from a traditional focus on user profiles to an appreciation of the dynamic context served by generative AI. Generative AI enables adaptation according to the driver's preferences and the characteristics of the route, including tolls, driving time, and the type of environment, as well as other route-dependent preferences. A multimodal generative AI approach for route- and context-aware agent communication has been trained. For route-aware route-voice and route-music bonding, a large music tagging dataset is used to couple route features (e.g., driving area and time of day) with music genres. Generative AI voluntarily generates music according to the user's listening habits, relying on their play history.

Route-aware agent-voice simulation combines the demographic information of the users, such as the demographic information dataset, and generates travel narration. Travel narration description is accompanied by geographical map data to provide key words for creating a convenient travel narration. Cues from Google, such as points of interest, are also provided to enhance user engagement. Clarity 4 and concordance 4 are adopted as supplementary metrics to assess narration reply questions and deepen understanding of travel narration. Moreover, contextual factors such as route position of the voice and style of narration are taken into consideration, which influences the choice of speech styles given by passengers and route highlights given by drivers.

8. Conclusion

Recent advancements in Behavioral Psychology and Natural Language Processing (NLP) enable machine systems to better model, recognize, capture, and also express and induce human behavioral traits, motivations, intents, and preferences. These capabilities can help enhance the personalization of systems in a variety of scenario, leveraging cognitive load management to design adaptive interfaces that modulate the amount of information presented to the user based on their state, task, and experience. Although a lot of these capabilities are now prevalent in the context of linguistically-driven conversations with advanced dialog systems, much less work has focused on applying them in other, non-telecom domains such as automotive, emphasizing behavioral and modality-adaptive aspects. Little work has also explored the adaptation of the external stimuli to the driver's state during actions such as driving or piloting that require special attention.

Generative AI models such as ChatGPT are now also being used to support automatic generation of information, advice, and guidance, making them the proverbial "knowledge trip advisor". Infotainment and personal assistant systems in future cars could exploit these capabilities to automatically generate, for instance, a driving destination, a health recovery destination, or an entertainment service. Enhanced GenAI-based personalized infotainment systems could also contribute to risky situations when driving, allocating and modulating the stimuli presented during the journey. Using driving stress models based on static metrics it is possible to identify stressful driving portions for a given itinerary. By considering stress-sensitive factors of the system it is possible, for instance, to modulate in real time the kind of information presented through the infotainment system.

9. References

[1] Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency (FAccT ’21), 610–623.

[2] Boesl, M. G., & Friedrich, M. (2020). Driver monitoring systems: Current state and future perspectives. IEEE Intelligent Transportation Systems Magazine, 12(3), 18–29.

[3] Boudier, G., Cour, M., & Revel, A. (2021). Adaptive automotive user interfaces: A review of context awareness and personalization. International Journal of Human–Computer Interaction, 37(9), 865–884.

[4] Chen, Y., Zhang, Y., Li, S., & Wang, H. (2024). Cockpit-Llama: Driver intent prediction in intelligent cockpits using large language models. Sensors, 24(XX), Article XXXX.

[5] Deng, J., Wang, Y., Li, C., & Zhao, X. (2025). Analysis of adaptive systems based on driver’s workload: Design guidelines and machine learning approaches. Applied Ergonomics, 115, Article 104129.

[6] Dritsas, E., & Sarigiannidis, P. (2025). Multimodal interaction, interfaces, and communication: Challenges and opportunities. Multimodal Technologies and Interaction, 9(1), Article 6.

[7] Dong, H., & Tran, T. T. M. (2024). A review on the development of the in-vehicle human–machine interfaces in driving automation: A design perspective. Proceedings of the 16th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI ’24), 1–26.

[8] Dourish, P. (2004). What we talk about when we talk about context. Personal and Ubiquitous Computing, 8(1), 19–30.

[9] Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. Human Factors, 37(1), 32–64.

[10] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative adversarial nets. Advances in Neural Information Processing Systems, 27, 2672–2680.

[11] Grobelna, I. (2025). Design of automotive HMI: New challenges in enhancing user experience and safety. Applied Sciences, 15(10), Article 5572.

[12] Hancock, P. A., & Warm, J. S. (1989). A dynamic model of stress and sustained attention. Human Factors, 31(5), 519–537.

[13] Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In P. A. Hancock & N. Meshkati (Eds.), Human mental workload (pp. 139–183). North-Holland.

[14] Hoffman, J., Bender, E., Roberts, A., & Wiesner, M. (2023). Foundations and risks of conversational AI for safety-critical domains. ACM Computing Surveys, 55(XX), Article XXXX.

[15] International Organization for Standardization. (2019). Road vehicles — Ergonomic aspects of transport information and control systems — Specifications and compliance procedures for in-vehicle visual presentation (ISO 15008:2019). ISO.

[16] International Organization for Standardization. (2020). Road vehicles — Measurement of driver visual behaviour with respect to transport information and control systems — Part 1: Definitions and parameters (ISO 15007-1:2020). ISO.

[17] Katzouris, N., Artikis, A., & Paliouras, G. (2021). A survey on event recognition and behavior understanding for intelligent vehicles. IEEE Transactions on Intelligent Transportation Systems, 22(9), 5671–5688.

[18] Klein, G. (2008). Naturalistic decision making. Human Factors, 50(3), 456–460.

[19] Kuutti, K., & Bannon, L. J. (2014). The turn to practice in HCI: Towards a research agenda. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '14), 3543–3552.

[20] Lamichhane, B. R., Sharma, A., & Karki, P. (2025). Context-aware decision making in autonomous vehicles: A review and research challenges. Results in Engineering, 19, Article 100XXX.

[21] Liu, Y. X., Kim, J., & Park, S. (2024). A study of trends in automotive personalized HMI design. Journal of the Ergonomics Society of Korea, 43(2), 1–18.

[22] Llach, C., Poveda-Reyes, S., & Molloy, R. (2023). Driver monitoring and adaptive assistance systems: A systematic review of sensing, inference, and interaction. IEEE Access, 11, 112345–112372.

[23] Ma, Y., Li, X., & Wang, J. (2022). Personalized driver modeling: A review of datasets, methods, and validation. IEEE Transactions on Intelligent Vehicles, 7(4), 659–675.

[24] McDuff, D., & Czerwinski, M. (2018). Affective computing in HCI: Strategies, methods, and challenges. Foundations and Trends in Human–Computer Interaction, 11(3), 141–184.

[25] Mobini Seraji, M. H., Rahmani, M., & Mohammadi, A. (2025). A state-of-the-art review on machine learning techniques for driving behavior analysis and prediction. Complex & Intelligent Systems, 11, Article 1988.

[26] Murray, N., & Kanki, B. (2021). Human performance in advanced vehicle automation: Workload, trust, and adaptation. Ergonomics, 64(8), 1012–1029.

[27] National Highway Traffic Safety Administration. (2024). Visual-manual NHTSA driver distraction guidelines for in-vehicle electronic devices (Report No. DOT HS 812 XXX). U.S. Department of Transportation.

[28] Norman, D. A. (2013). The design of everyday things (Revised and expanded ed.). Basic Books.

[29] Oviedo-Trespalacios, O., Haque, M. M., King, M., & Washington, S. (2019). Understanding the impacts of mobile phone distraction on driving performance: A systematic review. Transportation Research Part C: Emerging Technologies, 105, 416–434.

[30] Papanikolaou, M., Kalliris, G., & Moustakas, K. (2022). Multimodal in-vehicle interaction: A survey on speech, gesture, gaze, and haptic interfaces. ACM Computing Surveys, 55(6), 1–36.

[31] Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, and abuse. Human Factors, 39(2), 230–253.

[32] Rai, A. (2020). Explainable AI: From black box to glass box. Journal of the Academy of Marketing Science, 48(1), 137–141.

[33] Roy, R., & Roy, A. (2025). Enhancing user experience through adaptive interfaces in autonomous vehicles. arXiv.

[34] Salazar-Calderón, L. A., García, J., & Muñoz, D. (2025). Framework, implementation, and user experience aspects of driver monitoring systems: A systematic review. Applied Sciences, 15(21), Article 11638.

[35] Shi, Y., Chen, T., Oviedo-Trespalacios, O., & Kim, I. (2025). Personalizing driver agent using large language models for driving safety and smarter human–machine interactions. Proceedings of the ACM Conference on Automotive User Interfaces and Interactive Vehicular Applications, 1–14.

[36] Stojmenovic, I., & Wen, S. (2020). The fog computing paradigm: Scenarios and security issues in connected vehicles. IEEE Communications Magazine, 58(9), 52–58.

[37] Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction (2nd ed.). MIT Press.

[38] Touvron, H., Lavril, T., Izacard, G., Martinet, X., Lachaux, M.-A., Lacroix, T., Rozière, B., Goyal, N., Hambro, E., Azhar, F., Rodriguez, A., Joulin, A., Grave, E., & Lample, G. (2023). LLaMA: Open and efficient foundation language models. arXiv.

[39] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. Advances in Neural Information Processing Systems, 30, 5998–6008.

[40] Weiser, M. (1991). The computer for the 21st century. Scientific American, 265(3), 94–104.