MORPHIS: A Context-Aware AI for Dynamic Interior Morphing in Fully Automated Vehicles

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The mobility of the future with fully automated vehicles enables a complete rethinking of in-vehicle user spaces and interactions. We present an adaptive interior concept called MORPHIS in which a cooperative AI assistant continuously senses external influences (e.g., traffic density, notifications), vehicle state (e.g., charge level, range), and passenger condition (e.g., fatigue, mood) to dynamically morph physical and virtual cabin elements. To illustrate this concept, we simulate a scenario where five contextual inputs (sleepiness, work urgency, health stress, route distance, and email activity) drive a machine-learning model predicting optimal seat angle adjustments. Synthetic data spanning these factors are used to train a two-stage regression network. Early results demonstrate mean absolute error of ~2° in angle prediction and clear sensitivity to contextual triggers. We foresee extending this framework to examples like climate and lighting and envision multi-modal sensor data fusion for stable and precise AI suggestions, driving higher acceptance and competitive advantage for automotive OEMs.

Keywords: AI-driven Interior Morphing, Adaptive Vehicle Interior, Human–Machine Interaction, Sensor Data Fusion, Sleepiness Estimation.

1. Introduction

Level 4+ autonomous driving has morphed the cockpit from a static environment into a flexible, multi-purpose environment where occupants can seamlessly transition between work, relaxation, and social interaction. However, most semi-automated systems still rely on the driver, thus limiting the potential for uninterrupted tasks. While machine-vision–based solutions have achieved up to 98% accuracy in adjusting seat position to match occupant physique [8]. Yet these innovations only focus on a single element of the cabin without considering broader contextual factors. Further, context-aware interior adaptations like adaptive lighting systems that adjust brightness and color temperature according to in-car activities have been found to elevate user experience compared to manual control [9]. At the same time, studies emphasize that users still demand override options, signaling the need for hybrid systems that blend automation with user agency. Moreover, AI-driven personalization has begun to refine infotainment menus and proactive service suggestions [10]. Despite these advances, HMI adaptations largely occur independently of physical cabin changes, like seat or lighting adjustments. In this extended abstract, we introduce AI-driven Interior Morphing, a cooperative AI assistant that continuously monitors many factors to synchronize adaptive interior adjustments. The remainder of this paper is structured as follows: Section 2 details our methodology, section 3 dives into our implementation and section 4 is on various use cases.

2. Methodology

Our personalization pipeline comprises three core stages, see Fig. 1. First, a Base Prediction Model ingests real-time feature data: vehicle state, route information, sensor-derived passenger metrics and produces an initial estimate of the optimal cabin adjustments. In parallel, a User Model leverages passenger profile data (preferences, habits, health metrics) to generate a personalized bias vector. These two streams merge in a lightweight Final Personalization Model, which applies the user-specific bias to the base prediction without retraining the entire network, thereby minimizing compute overhead.

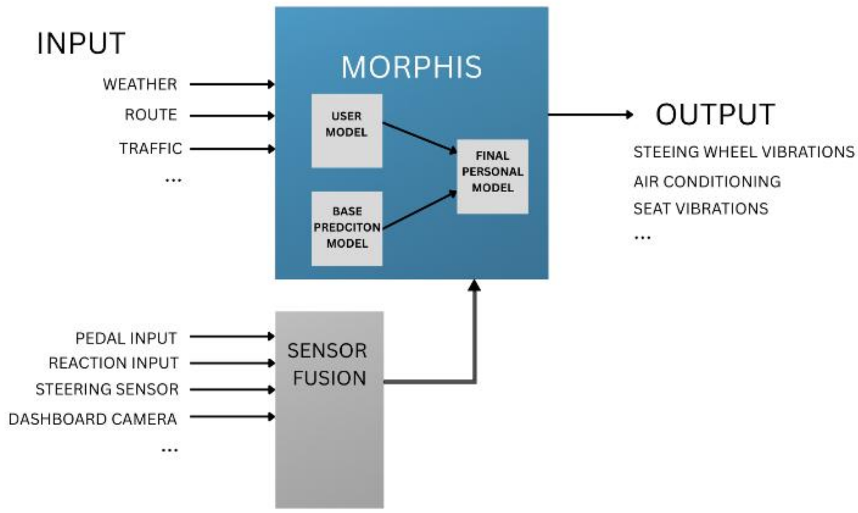


Figure 1: Basic pipeline of MORPHIS for an AI interior assistant using sensor data fusion for stable and precise suggestions.

Our architecture is based on ExcelFormer, a neural network surpassing GBDTs on tabular data [11]. A Manual User Intervention interface allows occupants to intervene at any time, feeding corrections back into the Final Model for immediate adaptation. The model's outputs are then written to the vehicle's state database, ready for actuation. This decentralized, modular design ensures that adaptation logic can be easily extended to new cabin elements (e.g. heating, display placement) and guarantees that every adjustment both reflects live context and conforms to individual user preferences.

3. Implementation

The core of AI-driven Interior Morphing is a modular, service-oriented architecture that ingests passenger and vehicle inputs, maintains a day-long task plan, evaluates rules against real-time context, and issues synchronized adjustments to the cabin's physical and digital actuators.

The Input & Context Manager orchestrates all incoming data streams. Passenger commands, whether via voice, keyboard or touch display, or gesture control, are funneled into a unified Natural-Language & UI Interpreter that translates them into structured task requests (type, timing, importance, and desired adjustments). Simultaneously, a Sensor-Fusion module continuously ingests vehicle bus data (location, velocity, drive/park/living mode, battery state of charge, and pre-crash warnings), traffic feeds, and external weather information. Wearable devices (like smart watches) and in-cabin sensors provide passenger state estimates (fatigue, mood), which are time-stamped and stored in a central Context Manager for downstream consumption.

The Task Planner & Rule Engine combines the passenger's day-long task plan (imported from calendars or defined manually) with a library of logical If–Then rules to determine which cabin adjustments should fire. Each task encapsulates its type (e.g. Work, Relax), scheduling (absolute time, trip mileage, or remaining time), priority, and associated adjustments. Rules—expressed with Boolean operators and weighted importance—evaluate current context (e.g. "if trip > 1 h on a highway and SAE level > 2") to produce activation scores. The Task Planner aggregates all active tasks and rule activations into a composite Adjustment Plan, weighting each suggested change by task priority and rule strength.

Once an Adjustment Plan is assembled, the Adjustment Coordinator dispatches commands to each subsystem actuator interface. Lighting adjustments set brightness, color temperature, and thematic "color concepts" (e.g. evening mode); audio modules select media sources, volume, and noise-cancellation settings; climate controls regulate temperature, ventilation, heated seats, and optional fragrances; seat and steering-wheel actuators adjust position and angle; and displays launch apps, arrange layouts, and modify brightness or contrast. To ensure occupant comfort, all physical transitions are smoothed via interpolation functions and constrained by subsystem-specific rate limits. A background Preference Learner drives personalization by logging manual overrides and explicit feedback. Periodically, it applies a lightweight reinforcement-learning update to rule importance weights and timing parameters, gradually aligning the system's default behaviors with the passenger's evolving preferences and routines. At runtime, the system follows a tight loop: 1. initialize with user profile and trip plan; 2. sample all context streams every 100 ms; 3. evaluate rules and synthesize the Adjustment Plan; 4. issue smoothed actuator commands; and 5. record overrides for offline learning. This layered, event-driven design ensures that voice, touch, and gesture inputs harmonize with vehicle state, external factors, and passenger physiology—delivering an AI-orchestrated, morphing interior that adapts fluidly to each occupant's needs.

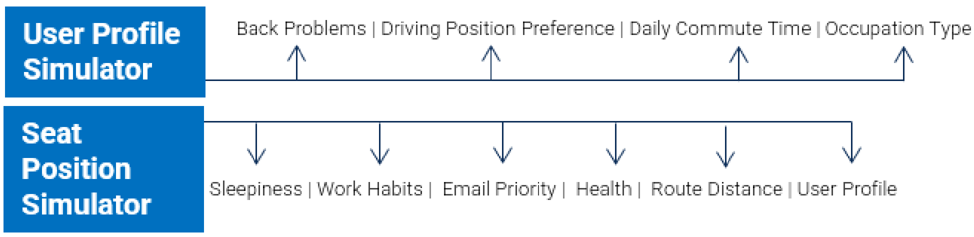
4. Use cases

The MORPHIS system offers a comprehensive approach to enhancing in-car experience, exemplified through its intelligent seat adjustment use case. This capability transforms the vehicle's interior into a responsive environment, proactively adapting to occupant needs. By integrating detailed user profiles, encompassing factors such as existing back conditions, driving preferences, and even daily routines (see Fig. 2A) with real-time physiological and contextual data, like sleepiness or current task demands, MORPHIS intelligently anticipates and executes optimal seat configurations. This goes beyond simple reactive controls, establishing a predictive system that maintains peak comfort and support throughout the entire journey, significantly improving the occupant's overall well-being.

Central to this is the system's ability to model and learn individual preferences over time, enabling dynamic and personalized adjustments to both seat angle and horizontal position. Through a simulated 24-hour cycle, MORPHIS demonstrates how it can dynamically adjust the seat recline based on typical human behaviors, such as morning commutes or periods of rest. This continuous, AI-driven optimization ensures that the seat is always configured to mitigate fatigue, promote proper ergonomics, and support various in-car activities, whether it is focused on work or relaxation. Ultimately, this use case illustrates MORPHIS's core promise: to deliver a highly intuitive and efficient driving experience by seamlessly orchestrating multiple cabin elements based on a holistic understanding of the user and their environment.

Integrating the visual representations (see Fig. 2), the mechanism behind MORPHIS's intelligent seat adjustment becomes evident. Fig. 2A illustrates the bipartite simulation framework: the "User Profile Simulator" on top captures static individual characteristics such as "Back Problems" and "Driving Position Preference," while the "Seat Position Simulator" below processes dynamic inputs like "Sleepiness" and "Work Habits." These inputs feed into MORPHIS's AI, enabling it to learn and predict optimal seat configurations. The result of this intelligent processing is vividly depicted in Fig. 2B, which presents a 24-hour seat angle pattern derived from MORPHIS's simulation. This graph showcases the system's ability to dynamically adjust the seat's recline throughout the day, responding to anticipated user needs and temporal habits, with shaded regions indicating the variation range.

A



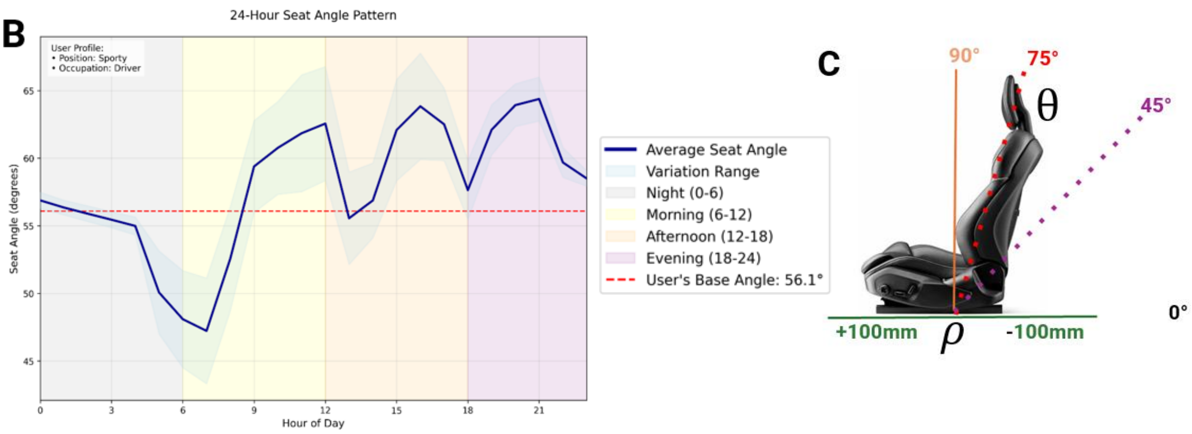


Figure 2: Functional Representation of the MORPHIS Seat Adjustment Use Case. (A) Simulated variables influencing seat adjustments within the MORPHIS system. (B) Hourly variation of average seat angle based on MORPHIS simulation data, with shaded regions indicating typical ranges for different times of day. (C) Visual depiction of the adjustable seat angle (θ) and horizontal position (ρ) in a car seat controlled by MORPHIS.

4.1 Vehicle-Integrated Sensor Data Fusion for Sleepiness Estimation

One way in which MORPHIS allows for dynamic interior adjustments that improve comfort, productivity, and safety in autonomously driven vehicles is to leverage sensor data already present in such vehicles to estimate passenger sleepiness.

MORPHIS uses a combination of self-report and objective measures for Defining and Measuring Sleepiness. The Karolinska Sleepiness Scale (KSS) [2] has been widely used in studies related to driving abilities to assess a person's level of sleepiness. It asks the participant to indicate their sleepiness on a 9-point scale ranging from “extremely alert” to “very sleepy, fighting sleep” during the five minutes before their rating. Further physiological signals can help to establish objective sleepiness levels. Electrooculography (EOG) via electrodes near the eyes tracks slow eye movements and blink patterns, which are proven indicators of drowsiness [12]. Similarly, remote photoplethysmography (rPPG) using a cockpit camera measures heart rate and its variability, which is a metric that changes significantly between alert and sleepy states [13]. By integrating these subjective and physiological measures, reliable and objective ground-truth labels can be established for sleepiness and used to train the AI of MORPHIS.

To estimate sleepiness without having these exact measurements, MORPHIS can analyze driving behavior and collect already available sensor data. Research shows that drowsy drivers make fewer small corrective steering movements (“micro-corrections”) compared to alert drivers [1]. These can be measured using steering metrics such as steering wheel angles, steering torque, cumulative steering corrections, or steering entropy.

Sleepiness also results in poorer lane maintenance. A metric called the Standard Deviation of Lane Position (SDLP) measures how much the car weaves within the lane. Under experimental sleep deprivation, SDLP increased as drivers got drowsier, correlating with higher KSS [1]. For instance, one study found average SDLP grew from ~0.19 m at KSS 1 (fully alert) up to ~0.47 m at KSS 9 (extremely sleepy) [1]. Additionally, an increase of unintentional lane departures has been shown to correlate with increased subjective sleepiness [3], which can be measured using lane-departure sensors or lane-keeping assistants.

Fluctuations in speed or pedal inputs can indicate that a driver is less alert. Fatigued drivers often show increased speed variability [4], which may be seen as drivers unintentionally slowing down or not being able to maintain steady throttle input. Additionally, drivers who had been awake for extended periods demonstrated delayed reaction times to traffic events [5]. Such delays can be measured through data on brake pedal reaction time, steering response latency to sudden danger on the road, delays in responding to collision warning alerts, or even reaction time to traffic lights or stop-and-go traffic.

However, we also need to measure sensor data when the driver is in autonomous-driving mode. An interior camera can continuously track visual cues of sleepiness in a non-intrusive way. For example, PERCLOS, the percentage of eyelid closure over time, can be computed from eye images and is widely regarded as a highly reliable indicator of fatigue [14]. The camera can also detect facial and head behaviors associated with sleepiness. Increased yawning frequency and subtle head nodding (the drooping or bobbing of the head during microsleeps) have been identified as important fatigue features [15]. Furthermore, advanced infrared cameras can capture facial temperature changes. One study found that skin temperature around the driver's eyes and nose drops significantly as they become sleepy [16].

The driver's posture and physical movements in the seat can change with fatigue. A driver's seating position can be monitored in vehicles embedded with pressure sensors in the seat cushion and backrest. Research has found that drowsy drivers tend to sink in their seats as they lose muscle tone and alert posture, shifting their weight forward and spending more time pressed against the seatback and headrest [6].

By intelligently combining and interpreting these diverse, vehicle-integrated sensor signals, we will analyze in the near future how MORPHIS can robustly detect passenger sleepiness in real time, enabling autonomous vehicles to dynamically adapt the interior environment.

5. Conclusion

We have outlined AI-driven Interior-Morphing and demonstrated its potential through various use cases. Embedding this capability in a software-defined vehicle unlocks dynamic comfort and productivity modes, transitioning cars into intelligent mobile workspaces. However, transferring this method to other scenarios presents technical challenges. Extending the framework to subsystems like climate and lighting requires not only integrating a wider variety of sensors and actuators but also developing robust control algorithms to ensure adjustments are synchronized and feel natural to the occupant. Future work must therefore include real-world user studies to validate the system's effectiveness and acceptance. Further expansion will focus on reinforcement learning for continuous personalization, allowing the system to learn highly subjective preferences and adapt to new contexts over time.

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