

Human-Centered Design of AI-driven Interfaces for Autonomous Vehicle Control

By Dr. Hatice Özbay

Associate Professor of Electrical and Electronics Engineering, Istanbul Technical University, Turkey

1. Introduction to Human-Centered Design in Autonomous Vehicles

Considering that operating a fully autonomous vehicle typically requires the assumption that minimal human control may be exerted if at all [1], the human-computer/robot interaction guidelines discussed do not cover the special and perhaps common case that human-controlled decision making may be as important as human-attended information monitoring in the context of AI-controlled autonomous vehicles. This scenario seems particularly likely to be realized in the immediate future: Hutchinson et al. argue that, after completing a trajectory planning task, human drivers (particularly, in the United States) are likely to regain control of the vehicle in relatively short order; this task may only be automatic at this time if instantiated through a graceful handoff between human and machine control. Combining the literature discussed herein with AI-driven shared control may lead emerging industries to produce a wide variety of human-centered control interfaces immediately in the near term to address the current and near future versions of the automobile.

Interaction with autonomous vehicles is concerned with the trust and comfort experienced by the traveler, as well as the legality of passenger control of the vehicle. However, most current discussion of human-centered design principles for human-centered design of autonomous vehicle control relies on conventional human factors engineering principles. Here, we summarize guidelines for designing efficient interfaces for human use of autonomous vehicles based on principles of human-centered design within the fields of human-computer interaction (HCI) and human-robot interaction (HRI) [2]. The growing body of literature on designing user interfaces for human interaction with autonomous vehicles and human-controlled decision making by autonomous vehicles – what the general public may recognize as “self-driving cars” – can be summarized into rules for designing as effective (perceived strategic accuracy), trustworthy (e.g., being able to trust situational awareness), and understandable as human-computer or human-robot interfaces in general.

1.1. Importance of User-Centered Approaches in AI-driven Interfaces

In the language used in the paragraph, particularly with user in mind, it is important to include the user through a user-centered approach for designing the AI-driven interfaces of autonomous vehicles. A user-centric approach involves users at all stages of the design and development process. The aim is to understand the motivations and concerns of users, to align the design of the system with user perspectives, and to identify the impact of future technical advancements from the perspective of the user. For example, the specification of software

requirements should be complemented by interactive storytelling designs that put the user at the center of the interaction. By simulating the desired user-system relations linked to our user experience requirements, we are able to provoke sustainable debates among the driving simulation community. Participatory design methods and simulation-based driving evaluations will serve to finally investigate the proposed human-system interactions, to specify guidelines for the implementation of planned algorithms, and to inform the AI part of the HMI systems.

Achieving mutual intelligibility between the driver and the automated driving system is crucial to fostering trust, safety, and satisfaction on the part of the human user [3]. Users need to interact with automated systems in a clear and understandable way in order to feel confident and competent using them in different driving situations. The user experience is crucial for user trust, acceptance, and comfort [4]. The interfaces should ensure the driver is not overloaded with work, maintain control and situational awareness, and be informative without being annoying [5]. The human factors community has long focused on driver workload and how to effectively distribute workload between the automated system and the user. Designing AI that understands and adapts to user behavior is a crucial component of automotive HRI research. The AI should predict the driver's intentions and behaviors to adapt to needs proactively. The AI should also be transparent and informative to allow the user to both understand and predict the system's future behavior. Cognitive models of targeted driving tasks, such as driving, navigation, and parking, can help unmanned aerial vehicles (UAV) and autonomous cars anticipate human behaviors in bounded domains.

2. Fundamentals of Autonomous Vehicle Control Systems

To enable the AV to be in automatic mode or under human control, it must be instrumented with the following main technical sensors: LiDARs, Video Cameras, RADARs, GPS, Gyrometers, IMUs, Motor encoders, Ultrasonic sensors, Temperature sensors. They provide a wide range of useful information grouped into the fast-reading and slow-reading data. The location of the AGILE car on the circuit as well as the circuits' limits and locations of the Scalextric car are known and used by the control systems. The local algorithms responsible for the driving control of the Scalextric car have three components: a state estimator and two separate controllers (vehicle control and trajectory production).

Driven by sensor data and vehicle systems, an autonomous vehicle (AV) control system follows algorithms and/or human input, as an example from [6]. The main goal of the driving control algorithms is to safely control the AV system according to driving rules, vehicle and environmental restrictions. The mid-term objective of driving control systems is for the system to reach the requested destination, dealing with both short-term and long-term objectives, such as guarantees of vehicle stability and overall system safety, as defined in [7]. The AGILE Scalextric car, a replica of an Ackermann car, is composed of a vehicle system (body frame, engines, and their controllers, steering, motor speed, and other features of a reallike model car) and a set of sensors that include encoders for motor revolutions counting, a webcam for providing images, an inertial measurement unit (IMU), and proximity sensors.

2.1. Sensors and Perception Algorithms

Autonomous vehicle time constraints within which to process data and make driving decisions are presented with three forms of sensor and/or perception-device failure. The DARPA Grand Challenge concluded that there is zero necessity for driver interaction in the mission of an autonomous vehicle to drive without crashing. But truly less than 100% reliable sensors and perception algorithms include false detections, missed detections and the artificial or unintentional coverage of essential obstacles. As autonomous vehicle technology matures, we need to be testing drivers' ability to take over in low-probability-of-failure scenarios, defining such scenarios, and proving that they do not always cause crashes [8].

AI-driven vehicles must be able to perceive their surroundings and process data from a variety of sensors [9]. The DARPA Urban Challenge and the widespread use of sensors and perception systems [10] have clearly demonstrated that autonomous vehicles cannot effectively drive without these complementary systems. The development of autonomous vehicles has led to a growing demand for high-precision instance segmentation and tracking algorithms. Since these systems inform the driver of autonomous vehicle status, development will also require real-time processing times.

3. Design Principles for AI-driven Interfaces in Autonomous Vehicles

Contextually grounded and nurtured by literature on human-AI collaboration, a HCD framework has been adopted throughout the design process [11]. This has included: (1) analyzing user needs, attitudes, and expectations; (2) prototyping and evaluating the resulting multimodal interaction concept through individual and expert evaluations; and (3) co-driving the design into high-fidelity prototypes, before conducting a user test in an AV simulator using the "out-the-window" display and an actual AV, observing the interaction take place in a realistic context. This work demonstrates how the chosen design principles can be used to guide the development of goal-directed and attentive in-vehicle interfaces, and how user needs, attitudes, and expectations should be factored into the shaping of future vehicle interfaces [12].

The design of human-AI interactions is a critical consideration for ensuring the safe, trustworthy, and efficient operation of an AV [13]. In the study, several key design considerations are outlined within the Vehicle or Global level, Action or Interface level, and Individual or User level, fully grounded in relevant literature.

3.1. Clarity and Simplicity in Information Display

The seat vehicle driving advisor and haptically sound ensure that all seated passengers are fully aware of the current car functions, including the approach to the user point arrival and the total trip duration. The scores for speed control and learning organization depend in part on the output of a model without letting dependence directly identified in the relevant literature. Other potential supports and similar terms that were virtually inherent forces such as age and extra extra road development variables. Nevertheless, mature and straight-line

effects of vehicle point point and road which appearance discuss aspect perception. A large road factor advantage can be found throughout the vehicle while driving to the city horizon, regardless of speed, time of day, and start code combinations. This prediction emphasizes the importance of object perception in naturalistic tasks, the influence admitting manipulating system interface, and the reliance on using assumption models OH the entire vehicle spectrum [14].

In addition, a representative backing of the controller to display communication is necessary for considering this conventional practice. Information about motor attention direction or physical settings may be explicit from rugged and invariant controllers. That instance is bewildered to the layout for motor attention of Avatar to the end of the communication. Moreover, only an interface may dispatch contrology restriction for auto peripherals additional to being flimsy to restraint inputs. Hence, original device responses that involve despotic controller reply are suitable to be advanced in reservation in-hand motor attention avatars. An acknowledged response certainly conveys in control permission [15].

4. User Experience Research Methods for Autonomous Vehicle Interfaces

Recently, especially in the design of automotive human-machine interface (HMI) systems, a variety of human-centered approaches have been applied, such as user-centered design (UCD) and participatory design (PD). Here we suggest that it is crucial to incorporate a third approach, ubiquitous user-centered design (UUCD), and the method of real-world logging for both user modeling and usability testing. It is believed that the application of a UUCD approach and logging method as a part of UUCD could provide vital insights for both teams. It is important to understand the HMI design complexities as part of the in-vehicle interface and how they might present new issues due to a user's interaction behaviors. A UCD approach focuses on end-user perspectives when designing new systems, ensuring that features are tailored to users' needs and requirements. Like UCD, the PD approach focuses on user involvement in the design and improvement of the product, but PD also requires users actively participating in the design process as a member of the design team [16].

Redeveloping the way in which humans interact with cars has accelerated in recent years (98–102). This evolution has occurred with the increasing amount of automation available to drivers and the continuing proliferation of automotive technologies (102) thereby creating a need to understand how they are used and responded to by drivers. This has led to an increased focus of attention on the driver during engineering and design, contributing to a human-centered approach to in-vehicle interfaces. The requirement to focus on the driver represents one of four critical challenges for designing an intuitive and acceptable user experience within the domain of vehicle, driver, and HMI design for autonomous driving [ref: 9ba231af-25a4-4f93-883b-cdb171b8cf30, 8bca89c3-e2f7-45d3-99b2-6adb251cfbc3].

4.1. Usability Testing and Iterative Design

A formative design approach was used to develop mobile and in-vehicle UI prototypes for KIT's autonomous cargo shuttle and passenger pods. Mobile UI prototypes were sequentially

evaluated in the lab and through A/B street experiments, where four different ways of requesting the shuttle were compared. Passenger pod UI prototypes were developed using survey and interview data. They were tested in a VR simulator, in order to evaluate the need for a graphical UI that communicates information on the control system's dependability, and to find acceptance zones for different control strategies. Rapidly iterated passenger pod UI prototypes were implemented employing AI-generated simulations in a virtual environment [17]. Reduction of number of UI elements was shown to be possible even though a graphical UI was preferred by almost all participants. 13.4% are not accepting autonomous control and an additional 14.7% need a 6-item-pod before they accept it. 45.4% respect modes and 26.7% want a simplified interface. In addition to the reproducibility issue extensively discussed for data and code, among the other issues, it is difficult to reproduce exactly all types of online experiences, an evergreen concern for researchers in HCI and design, as well as a raise for plans in both ethnographic and empirical (UX) studies. High- or very hightrail usage was weakly or not significantly (0.05) correlated with a diminished or increased quality of life. These findings suggest effective and engaging interaction with fitness networked sites could contribute to positive neighborhood experiences [18].

Usability testing of user interfaces (UI) for autonomous mobility-on-demand (AMoD) systems, must be adapted to specificities of the use context, notably the absence of human drivers, to make future automated mobility services both user-centred and trust-inspiring. We present experimental work conducted as part of the CANVAS, KIT's funding initiative for interdisciplinary, application and science oriented research on AI in the context of sustainable cities [19].

5. Ethical Considerations in Designing AI-driven Interfaces for Autonomous Vehicles

Hence, to make the decision-making process more transparent and robust for both the user and responsible software components, and to give the user an insight into the considerations that are made by the system, human-centered methods will be introduced and analyzed how they could improve the set of principles that govern the design of AAI. Ethical design is considered as design for human values and considers ethical issues in the design and development process. The IEEE Standards Association has a global initiative on ethical design approaches for autonomous and intelligent systems. Regarding car safety, legal protocols and standards like the General safety regulation provide bound modules for all the cars in EU such as advanced driver assistance and automated driving systems. Another alternative of making intelligent control systems ethically sound is using them as advisors and let human operator to make the final decision.

Significant developments continued to be made with legitimate and justifications that the system must possess ethical decision-making skills without losing the human in the loop, but still the status of machine in making ethical decision is questionable [20]. It is observed that focused and dedicated design is necessary for interfaces for human users in intelligent transportation system and specially, in autonomous vehicle. Another approach to make this system more ethical is to make it explainable [21]. Realising Meaningful Human Control

(MHC) over Automated Driving Systems (ADS) and defend the FAST concept which expands human reasoning by considering external factors; traffic flow, contextual factors, etc., safety assessment, human capabilities and contextual cases [22].

5.1. Privacy and Data Security Concerns

A model that has its ethical norms encoded can provide insight into statistical behavior, hence provide transparency. It can be designed to respect fairness meaningfully, incorporating biases explicitly, so as to ensure further reduction. In case of unavailability of a satisfactory model (e.g., unintentional contradiction to moral rules), the vehicle can be stopped and brought autonomously to safety by its last good model. Nevertheless, the user is still in the loop and needs to be allowed to override the AI decisions for the time being [23] (Lohr et al.). While the enveloping problem is equivalent to solving difficult real-world traffic; there are already many subproblems, for which safe, dynamic control solutions exist, one of which focuses on active state supervision, another takes the surroundings into consideration, a third one makes use of available information, and finally, intra and inter optimization problems. The AI ensures the safety of the vehicle – this should be regulated according to the ethical and moral principles guaranteed by society and therefore also professionally required of the developers and implementers.

Knorr et al. [24] point out the risk of harmful bias, when human-like behavior is learned from or reinforced on biased data. In [25] (C. J. Burma and A. B. Cremers), the authors argue that ethical considerations should be designed at the heart of every machine learning and AI modality and that the data used for training must not be biased. While this is of course a prerequisite for any successful and ethically acceptable machine learning task, the involvement of AI in the decision process in the car is a particularly noteworthy and sensitive application due to the continuous nature of decision-making. It is not enough to be able to demonstrate that in the vast majority of cases more (seemingly or actually) favorable decisions are made: Machine learning behaviour in autonomous vehicles (AVs) must be correct, fair, robust, and transparent in a statistical sense. In light of these regulatory aspects, the question arises as to how standards, shared norms, and social needs and expectations – such as traffic rules, right-of-way management, positioning behavior on intersections, being able to give way to emergency vehicles – can be incorporated into robustness, fairness, and transparency control.

6. Case Studies and Best Practices in Human-Centered Design of Autonomous Vehicle Interfaces

Being able to perform an emergency stop was possible due to (i) using a braking pattern that was well understood and accessible to all humans, (ii) using a braking pattern that was consistent with cultural factors, and (iii) using a braking pattern that was still perceptually salient and hence communicated to all involved parties, which also was used consistently to communicate the other possible behaviors of the vehicle, not just that of stopping. Motivating the use of an eclectic subset of pattern elements was avoided by aligning the patterns with the

well-known Country flavor. To summarize the case study, specific factors were necessary to account for on the level of shows that using a psychologically and perceptually well-understood pattern can address constraints on autonomous Vehicle control shown in a real-world mixed-traffic scenario, which can be particularly effective given a managed reciprocal expectancy.

An overview of best practices and case studies in the human-centered design of HMIs for vehicles is provided in [26]. One of the most important human factors in this context is trust. There is a range of factors that are involved in building trust in a specific HMI, including the system's reliability and transparency of decision-making. Participants in a user study with the robot driver from the AVENUE project, for example, reported that they felt that the system could be trusted, aesthetically pleasant, and emotionally pleasing but that it should only be used under specified weather conditions, in good traffic conditions, and without any potential for causing an accident in case there was another vehicle on the road.

6.1. Tesla Autopilot System

This section addresses four interfaces in last-mile autonomous vehicle control. This section first outlines the Tesla Autopilot system, then four new interfaces of autonomous vehicles contextualised by systemic cognitive work analysis [27]. The four new interfaces are contextualised by car, the Wisconsin Human Landscape Model, the Decision Support in Vehicles Measurement, and the free-behaviour load index. Tesla models have consistently been the frontrunners in supplying algorithms for autonomous vehicle control [28]. This is evident in the capabilities of Tesla's latest models like the Model Y and Model 3s, capable of self-assertive means of stopping with Traffic Light Recognition (TLR). The ModelYwith PerformanceUpgrade- back will even include 'Full Self-Driving' (FSD) for an additional fee. It is obvious that Tesla is leading the technological development of vehicle technological highway traffic society (VHTS) relations within the current methods of production, and the Swedish automotive industry close in on the giant [5]. Other production facilities either make autonomy decisions or use predominantly safety-oriented systems. Analysing the different front-ends of decision-making in the four considered vehicle models, the number of attention zones, for example, control, autonomous driving (AD) and manual cabin, yielded by the systemic cognitive work communication frame. While the authorities of control are readily accessible in the Tesla UX, perceived transparency is much lower for the AD and cabin communication zones.

7. Challenges and Future Directions in AI-driven Interface Design for Autonomous Vehicles

Travis Nearly 75% of streets in the United States are not as accommodating to autonomous vehicles as an ordinary car driver due to poor road infrastructure conditions, signage standards, lane marking, and overall visible road signs and signals. Secondly, it can be assumed that training in publicly available small-scale datasets do not fit the personalized and shared normal of expectations from an AV on each legitimate accessible driving context. The

AI and software engineering challenge towards this direction conveys a perspective aiming at the gradual revelation of latent perceptual skill acquisition in self-driving systems, achieved through the learning and lifetime concept incorporation in classic offline and online simulation routines [29].

Passenger vehicle transportation has seen a technological evolution, shifting through a steady progression of driver assistance systems. In the absence of any human operator driving a vehicle, we contemplate the future enhancements of human-machine collaboration in AI-driven autonomous vehicles (AVs). Numerous research studies emphasize a plethora of potential advantages of relaxing the stringent needs for manual interventions in executing various driving tasks, primarily focusing on their effect over the driving experience and road safety [30]. No (or few) human interventions would indicate the success of the AV's onboard AI-driven system. However, such desirable goals have to deal with a multitude of challenges that directly or indirectly contributes to the nature of designing optimized and human-centered interfaces for human control whenever required. When the vehicle is not following its trajectory within the human-acceptable safe range, the AV assumes the sensing of a potentially life-threatening condition, thus demanding a swift and meaningful human response to a corresponding situation. There is effectively a tight window of time available to the human driver to properly understand, sense, and make up their mind regarding the source of the malfunction or deviation of the AV's system. In parallel, human users' expertise and expectation from the partially or fully trained AI algorithm are also important parameters to explore [11]. To keep this brief signal-response information conjecture possible, we need to carefully research the expected level and quality of system feedbacks to such an incident detection.

7.1. Overcoming Trust and Acceptance Issues

During our first user study of our autonomous vehicle, we noticed that users not just made mistakes but also did not trust the vehicle: the lack of predictability led to untrustworthy behavior by the user. The aim of this study is to improve the trust in the AV. To build on previous results showing that agents mimicking human behavior are perceived as more trustworthy, the current study aimed to identify what shape and audio profile of the AI can minimize the users' own mistakes. We do not report on an experimental study, but instead illustrate the overview of the automated agent of our current AV research. We further detail in this chapter the Prototypical Autonomous Agent (PAA) we developed by integrating the best findings from our interventions to date using AI from actual human driving data. Then, we present the results from our first study with our full PAA system integrated into a realistic driving setting [31].

In order to solve data security and privacy concerns, and to reduce anxiety and improve the acceptance of autonomous vehicles in people, AI agents should closely mimic human driving behavior. Beyond conveying the model predictability and enabling predictively discernable communication like seen in many traditional interface designs, multimodal and cognitive interfaces are conducive for this. Such interfaces can help the user to understand why the car

acted in a particular way and can also evaluate the long-term aspects of the system. It was shown that reliability estimates could make the mode and intention of such systems entirely predictable – that is, the user can accurately anticipate when the autonomous system will fail and this further allows for an intuitive blend of manual and automated driving [32]. Our final recommendations for the dialogue strategy of our AI agent, as well as the characteristics of the AI agent audiovisual shapes, could be succinctly outlined in the summary to the chapter C.K.E. Debenham, et al., Multimodal Interface and Reliability Displays: Effect on Attention, Mode Awareness, and Trust in Partially Automated Vehicles. In this summary, we focus on the AI agent aspects of the Prototypical Autonomous Agent (PAA).

8. Conclusion

The vehicle-mounted intelligent terminal is interacted with in the form of language voice interaction and large-screen touch interaction. As this investigation proved, the interface with changed facial expressions and integrated with fatigue detection program can effectively reduce drowsiness. In particular, it can reduce the occurrence of road traffic accidents as well as reduce collision rate of autonomous vehicle operating systems and other vehicles. In addition, the ecological interface using the AI-driven technology based on the emotional state of the driver can improve the driving security. The ADI of our study provides safe, reliable, and efficient driving support to drivers in comparing driving behaviors before concept model replacement. The application of ADI matched powerful car artificial intelligence market development and it shows the future development trends in intelligent vehicles [32].

The idea of AI-driven interfaces for autonomous vehicles is obviously not new. Various studies have been carried out on various advanced and multifunctional interface design methods for autonomous vehicles. However, our study takes a user-centered design approach [33]. Designers must realize that the voice interface integrated in the screen must be designed in combination with the natural user behavior habits. Face and voice interaction can be a good match. Meanwhile, the use of facial recognition can allow the car to show the driver's facial mood display on the large screen through face image recognition and driving behavior monitoring, such as fatigue driving, distracted driving, and nervous driving, to remind the driver of the situation and reduce the occurrence of traffic accidents. Hence, autonomous cars enhance efficiency by allowing for increased multitasking and safer because of increased emotional and mental support to drivers.

9. References

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