# Trust-Building in Level 4 Automation by Intent Communication: In-Vehicle HMI Design, Passenger Trust, and Visual Attention

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**16. Abstract**
At SAE Level 4 automation the vehicle occupant becomes a passenger with no driving role, no fallback obligation, and no expectation of takeover. The passenger cannot intervene with the driving and thus must rely on trust. Here, it is the in-vehicle human-machine interface (HMI) that is the primary channel through which the vehicle can make its perception and intent legible. Passenger-facing HMI is sparsely researched relative to external interfaces and to drivers at lower automation levels. This project addressed that gap in three tasks. A systematic review following PRISMA searched seven databases, screened 3,364 records, and synthesized 37 studies on how in-vehicle HMI modality, content, and quality shape passenger trust. Guided by that synthesis, three in-vehicle HMI conditions (auditory, visual, and multimodal) were built in Unity and integrated with a high-fidelity driving simulator, that communicated the vehicle's perception and intent five seconds before every maneuver. This was experimentally evaluated with thirty-six participants who rode as rear-seat passengers through a seven-minute Level 4 drive containing eight scenarios, with survey and head-mounted eye-tracking measures. Reported trust increased significantly from pre-drive to post-drive in all three conditions. The multimodal interface produced significantly higher trust and perceived system transparency than the visual interface, with no penalty in workload or usability. HMI modality shifted visual attention only toward the in-vehicle display, and trust was negatively correlated with time spent monitoring that display. Passenger scanning remained anchored on the forward roadway and varied with the driving scenario rather than with the interface. Communicating intent builds passenger trust irrespective of channel, and redundant multimodal delivery builds the most trust.

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## About NEUTC

The New England Regional University Transportation Center (NEUTC) is a multidisciplinary consortium committed to addressing the pressing issue of traffic safety. Our objective, in line with the Infrastructure Investment and Jobs Act (IIJA), is to drive transformative research, education, and technology transfer to address critical traffic safety needs in a time when roadway fatalities are distressingly high.

Our research and educational activities at NEUTC are guided by four principal safety themes, each addressing a critical challenge in transportation safety. These themes capture the various integral components of the transportation system, focusing on technology, infrastructure, vehicles, and users with a commitment to community engagement. Our overarching theme is promoting safety, with the common underlying science being the study of behavioral, systemic, environmental, and mobility-driven factors on safety.

## Disclaimer

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## Motivation

Motor vehicles are becoming increasingly automated, and vehicles capable of SAE Level 4 (L4) automation are being publicly deployed. An L4 automated vehicle (AV) performs the entire dynamic driving task within its operational design domain without human intervention (SAE International, 2021), and such vehicles now operate as driverless taxis and automated shuttles in a growing number of cities. The scale of these deployments is expanding quickly: as of May 2026 one leading operator reported a commercial fleet of approximately 4,000 driverless vehicles (Elias, 2026), and through March 2026 had accumulated more than 220 million rider-only miles with no human driver behind the wheel (Waymo, 2026).

The expansion is motivated by the potential of automation to improve roadway safety and mobility. The United States records approximately 40,000 roadway deaths annually, and driver-related factors have been identified as the critical reason for the crash in approximately 94% of cases (NHTSA, 2018). Because L4 automation removes the human from the driving task, systems that operate more safely than human drivers could reduce crashes and resulting injuries and fatalities, with early evaluations of deployed L4 fleets suggesting that they outperform human benchmarks on several crash measures (Kusano et al., 2025). Automation may also expand access to transportation for older adults and people with disabilities, who may face barriers to using conventional or shared modes. These benefits, however, are realized only to the extent that the technology is adopted and used.

L4 automation also changes the role of the person inside the vehicle. In manual and partially automated driving, the human controls the vehicle or supervises the automation and stands ready to intervene. At L4 the occupant has no driving role, no fallback obligation, and no expectation of takeover, and in most real deployments rides in the rear of the vehicle. Having no means of intervening, the passenger must instead rely on trust, defined as the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability (Lee & See, 2004). Trust that is poorly calibrated carries risk in both directions: passengers may reject a capable system, or rely on it in circumstances where it is not capable (Hoff & Bashir, 2015; Merritt et al., 2015). Public willingness is another constraint, with survey evidence indicating that a majority of Americans are unwilling to ride in a driverless vehicle. Because the passenger cannot act on the vehicle, the in-vehicle human-machine interface (HMI) becomes the primary channel through which the vehicle's perception and intentions are communicated.

Despite this, passenger-facing in-vehicle HMI remains comparatively underexplored. Much of the research on communicating AV intent has addressed external road users through external HMI (Bindschädel et al., 2023; Yassien et al., 2023), and reviews of in-vehicle HMI have focused largely on drivers at lower levels of automation, where a takeover may be required (Wang et al., 2024). This project addressed that gap by asking two questions: (a) how is AV intent communication related to passengers' trust and acceptance, and (b) what interface features contribute to trust building? The work aligns with the overarching NEUTC theme of Promoting Safety and with the themes of Promoting Automated Vehicle Safety and Developing Smart Infrastructure and Connected Systems, and it supports the USDOT research, development, and technology goals of Safety and Transformation by addressing the acceptance and adoption of advanced vehicle technologies.

## Executive Summary

### Research Approach

This research project was undertaken via three coordinated tasks. The first was a systematic review of how in-vehicle HMI shapes passenger trust at SAE Levels 4 and 5, conducted to establish the state of the evidence and to derive design requirements. The second was the design and development of three in-vehicle HMI conditions, using the Unity development environment, together with a simulated L4 drive implemented in a high-fidelity driving simulator. The third was a between-subjects experiment in which 36 participants experienced that drive as rear-seat passengers under one of the three conditions, with survey measures collected before and after the drive and eye movements recorded throughout. The gaze data were analyzed at two levels: conventional aggregate metrics describing where passengers looked and for how long, and a sequence-sensitive characterization of scanning that modeled each fixation sequence as a first-order Markov chain over areas of interest and summarized the result with its stationary distribution and with two measures of gaze entropy. These two levels answer different questions and, as reported below, yielded complementary results.

### Evidence Base: In-Vehicle HMI and Passenger Trust

The systematic review followed the PRISMA (Page et al., 2021) guidelines. Searches covering publications from 2000 through June 3, 2025 were run across seven databases spanning engineering, psychology, and transportation safety, combining three concept groups: vehicle automation, trust and related constructs, and communication interfaces. Eligible studies were those that were peer-reviewed, English-language, original empirical work with human participants addressing SAE L4 or Level 5 automation; reviews, conceptual papers, dissertations, and studies of external HMI were excluded. The searches returned 3,364 records, of which 37 were retained for synthesis after title screening, abstract screening, removal of duplicates, full-text review, and backward citation tracing. Every included study was published between 2016 and 2025. Twenty examined visual-only interfaces, eight auditory-only, and eight multimodal or cross-modal combinations; most were conducted using driving simulation methods

Three conclusions from the synthesis informed the design of the present experiment. First, modality shapes passenger trust. Visual interfaces generally increased trust when they conveyed both what the vehicle perceived and what it intended to do (Ekman et al., 2016; Ma et al., 2021; Oliveira et al., 2020), though the benefit was conditional on consistency between display and vehicle behavior, with one test-track study finding visual HMI underperforming a no-HMI baseline where displayed path and actual motion diverged (Basantis et al., 2021). Auditory channels reliably supported trust (Du et al., 2019; Fagerlönn et al., 2020), and multimodal interfaces generally outperformed unimodal ones (Ma et al., 2025), although this advantage appears conditional on the passenger's attentional state and may not hold under non-driving-related task engagement (Hong et al., 2025). Second, the combination of vehicle perception, intent, and rationale was the most trust-relevant content, with additional information raising workload without corresponding gains (Li et al., 2023). Third, explanations delivered before an action supported trust more effectively than explanations delivered afterward (Atakishiyev et al., 2024; Du et al., 2019; von Sawitzky et al., 2019). Accordingly, the interfaces developed in this project communicated both perception and intent, delivered every message before the corresponding maneuver, and manipulated modality while holding content and timing constant.

## Interface Design and Experimental Platform

Three in-vehicle HMI conditions were developed, differing only in modality through which the vehicle's perception and intent were conveyed. The AV's intention and explanation were delivered five seconds before the vehicle initiated the corresponding action, and message content and trigger timing were tied to scenario event markers scripted in the simulator and were identical across conditions, so that the manipulation was solely the channel of delivery. The visual HMI was presented on a 10.9-inch tablet mounted on the front-seat headrest facing the rear-seat passenger (in-vehicle display). Built in Unity to mirror the simulated environment, it showed a simplified elevated third-person rendering of the driving scene containing the ego-vehicle (the AV), roadway geometry, traffic signals, and detected road users, with a directional arrow projected onto the roadway ahead of the ego-vehicle to indicate its intended trajectory and upcoming maneuver. Collider-triggered state changes kept the display synchronized with events in the simulated drive. The auditory HMI delivered spoken explanations generated by a text-to-speech system and played through the cabin speakers, with the in-vehicle display switched off. The multimodal HMI presented both renderings together, temporally aligned (Figure 1).

The experiment ran on a fixed-base, high-fidelity driving simulator (Realtime Technologies, Inc.) built around a full 2013 Ford Fusion cab and operating on the SimCreator engine, with L4 automated driving supplied by the SimDriver module and configured to match the functional scope defined for that level in SAE J3016 (SAE International, 2021). Five forward projection screens provided a 330-degree field of view, with rearward views rendered in the mirrors and on a projection screen behind the cab, and a five-speaker system reproducing external sounds alongside two in-cabin speakers for in-vehicle audio. Eye movements were recorded at 50 Hz with Tobii Pro Glasses 3, a head-mounted eye tracker. The simulated drive took place in an urban and suburban network with moderate traffic and posted speed limits of 25 to 35 mph. The automation engaged itself at the start, performed the entire dynamic driving task including navigation, sign recognition, and interaction with other road users, and brought the vehicle to a stop at the end, with no human intervention and no driver behind the wheel. The drive lasted approximately seven minutes and contained eight scenarios in a fixed order identical for every participant: a pedestrian crossing, a construction zone, a lane change, a left turn, a parked bus, an emergency vehicle on the shoulder, a second left turn, and a second pedestrian crossing.

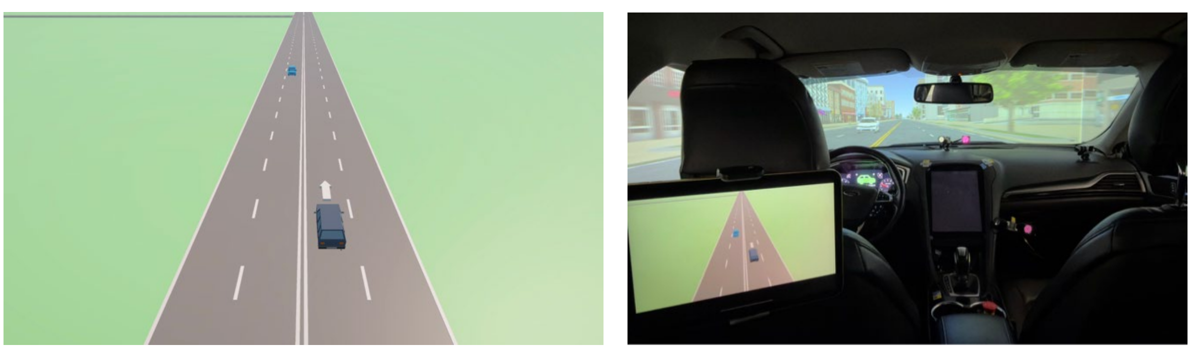

**Figure 1. The visual HMI rendering and the participant's point of view showing the in-vehicle display.**

## Participants and Measures

Thirty-six participants (17 female) were recruited from students and staff at the University of Massachusetts Amherst and randomly assigned to one of the three interface conditions, twelve per condition, with mean ages of 24.2, 22.5, and 22.5 years in the auditory, visual, and multimodal conditions respectively. An a priori power analysis conducted in G*Power (Faul et al., 2007) indicated twelve participants per group. Because participants took part as rear-seat passengers, a driver's license was not an eligibility requirement, although 33 of the 36 held one; 32 of the 36 reported no prior exposure to automated vehicles. All participants gave written informed consent, the protocol was approved by the University of Massachusetts Amherst Institutional Review Board (#7221), and participants received $20. Participants completed a pre-drive questionnaire and a single-item baseline trust rating, were fitted with the eye-tracking glasses and calibrated, and were then seated in the rear passenger seat and briefed. They were given no instruction to monitor the drive or the interface, so as to avoid priming their visual attention toward these elements, and were not permitted to engage in non-driving-related tasks.

Post-drive survey measures comprised trust, assessed with the 20-item Trust in Self-Driving Vehicles scale (Robertson et al., 2023) and with a Trust in Automation measure; perceived system transparency, adapted from Choi and Ji (2015); intention to use; workload, assessed with the NASA-TLX (Hart & Staveland, 1988); and usability, assessed with the System Usability Scale (Brooke, 1996). Open-ended responses were also collected. Gaze measures were defined over five areas of interest —windshield, in-vehicle display, instrument cluster, and left and right windows — with a sixth residual category used in the sequence analysis. A glance was defined as the interval from the start of the saccade leading into an area of interest to the end of the last fixation within it. Aggregate measures were the percentage of glance duration and the glance count per area of interest; sequence measures were the first-order Markov transition matrix, its stationary distribution, and normalized stationary gaze entropy (SGE) and gaze transition entropy (GTE). Analyses were conducted in R (R Core Team, 2023).

**Finding 1: Communicating intent builds trust, and multimodal HMIs are most effective**

Reported trust increased significantly from before to after the automated drive for every interface, with mean increases of 0.58 in the auditory ($p = .027$), 1.58 in the visual ($p = .004$), and 1.80 in the multimodal condition ($p < .008$); baseline trust did not differ across conditions. That is, exposure to a L4 drive accompanied by communication of the vehicle's perception and intent was associated with improved trust regardless of the channel of delivery. Modality nonetheless differentiated the conditions (Table 1). Post-drive trust differed significantly across conditions, $F(2, 33) = 5.05$, $p = .012$, $\eta^2 = 0.234$, with trust in the multimodal condition ($M = 5.80$, $SD = 0.52$) significantly higher than in the visual condition ($M = 4.63$, $SD = 0.90$), $p = .009$, $d = 1.59$. Perceived system transparency followed the same pattern, $H(2) = 8.92$, $p = .012$, with the multimodal condition again significantly higher than the visual condition. The parallel between the two measures is consistent with the proposition that transparency can engender trust. Intention to use, usability, and workload did not differ across conditions, indicating that the advantage of redundant multimodal delivery came without a cost in workload or usability.

One result ran counter to expectation: trust in the auditory condition was numerically higher than in the visual despite the visual interface presenting considerably richer information. The difference was not significant, but it is consistent with prior work in which an auditory interface outperformed a visual one on trust, comfort, and perceived safety (Basantis et al., 2021). A plausible account is that spoken explanation is received without additional effort, whereas visual information must be looked at, interpreted, and verified against the roadway. Open-ended responses were consistent with this. Participants in the auditory condition asked for a supporting visual display to ground the spoken cues; participants in the visual condition asked for auditory feedback and commented on the placement of the display; and participants in the multimodal condition described a functional division between the channels, using the display to understand the environment and the auditory channel for operational status. Across all conditions participants asked for more demanding scenarios that would test the limits of the automation.

**Table 1. Effect of HMI modality on survey measures.**

| Measure | Test | Statistic | p | Post hoc |
|---|---|---|---|---|
| Trust in Self-Driving Vehicles | One-way ANOVA | $F(2, 33) = 5.05$, $\eta^2 = 0.234$ | .012 | Multimodal > Visual (p = .009, d = 1.59) |
| Trust in Automation | One-way ANOVA | $F(2, 33) = 2.36$ | .110 | — |
| System transparency | Kruskal–Wallis | $H(2) = 8.92$, $\eta^2H = 0.210$ | .012 | Multimodal > Visual (p = .009) |
| Intention to use | One-way ANOVA | $F(2, 33) = 0.34$ | .713 | — |
| Usability (SUS) | Kruskal–Wallis | $H(2) = 2.37$ | .306 | — |
| Workload (NASA-TLX) | Kruskal–Wallis | $H(2) = 4.07$ | .131 | — |

### Finding 2: What passenger's visual gaze reveals about trust

Because the eye-tracking data violated the assumption of normality, aggregate glance measures were analyzed using a two-factor aligned rank transform analysis of variance (Wobbrock et al., 2011) with interface modality as a between-subjects factor and area of interest as a within-subjects factor. The analysis returned a significant modality by area-of-interest interaction for both the percentage of glance duration, $F(8, 132) = 5.44$, $p < .001$, and the glance count, $F(8, 132) = 5.75$, $p < .001$. This finding is informative, in that modality did not shift attention uniformly, but selectively, and post-hoc comparisons localized the effect entirely to the in-vehicle display (Figure 2). The percentage of glance duration directed at the display was 1.21% in the auditory condition, 6.75% in the visual condition, and 4.92% in the multimodal condition, with glance counts of 7.9, 28.7, and 23.2 respectively; the auditory condition was significantly lower than both others, as expected given that no content was presented on the display in that condition. No significant differences between conditions were found for the windshield, the instrument cluster, or either side window.

Two observations follow. First, the visual and multimodal conditions did not differ from each other on either display measure, which suggests that adding spoken explanation complemented rather than substituted for visual inspection of the interface. Second, participants in the auditory condition still directed roughly eight glances at a display that was switched off and showed a tendency toward greater attention to the instrument cluster, indicating that the physical presence of a screen attracts attention independently of its content and that its absence prompts a compensatory search elsewhere in the cabin. Trust and interface monitoring were inversely related: in the multimodal condition trust was significantly negatively correlated with the percentage of glance duration on the display, $r = -.58$, $p = .049$, and with the number of glances at it, $r = -.81$, $p = .002$, with negative but non-significant correlations in the visual condition. Passengers who reported greater trust spent less time checking the interface, consistent with the use of monitoring frequency as a behavioral index of trust in automation (Hergeth et al., 2016), although these cross-sectional correlations cannot establish the direction of the relationship.

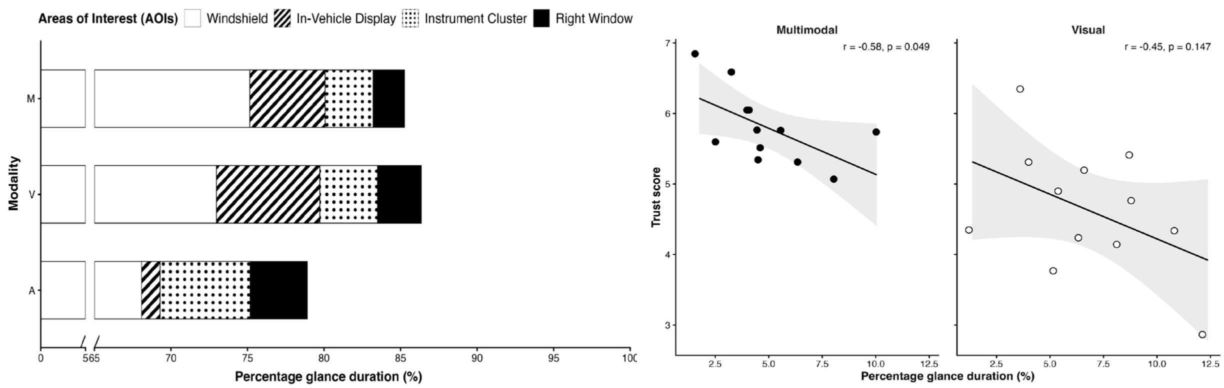


**Figure 2. % of glance duration across AoIs by modality (left); Relationship between % glance duration and trust (right)**

## Finding 3: Visual gaze is governed more by the scene, and not the interface

Each participant's fixation sequence was modeled as a first-order Markov chain over the six areas of interest, an approach with a long history as a descriptive framework for the temporal structure of visual scanning (Ellis & Stark, 1986), with the first-order assumption supported by a likelihood ratio test against a second-order chain (Anderson & Goodman, 1957). Scanning was organized around the forward roadway in every condition. The windshield had by far the highest self-transition probability (0.81 to 0.83 across conditions), every other area of interest was more likely to transition back to the windshield than to any other region, and the stationary distribution placed 58.3% to 63.6% of long-run fixations on the windshield (Figure 3). Rather than moving laterally among peripheral regions, gaze returned repeatedly to the roadway, which functioned as an anchor state. This is notable because the participants were rear-seat passengers with no driving responsibility and no driver in front of them, yet they maintained a road-anchored gaze resembling the supervisory pattern documented in manual and partially automated driving. Residual habit, active trust calibration during a novel first exposure, and a general disposition to attend to the most dynamic region of the scene are plausible explanations.

The influence of the driving scenario and of interface modality on scanning was tested with linear mixed-effects models of normalized gaze transition entropy and stationary gaze entropy, each with modality and scenario as fixed effects and a by-participant random intercept. Both models returned a significant effect of scenario, $F(7, 231) = 9.14$, $p < .001$, $\eta^2p = 0.217$ for transition entropy and $F(7, 231) = 5.50$, $p < .001$, $\eta^2p = 0.143$ for stationary entropy, and no effect of modality and no interaction. Entropy was highest at the first pedestrian crossing and the construction zone, the most visually involved situations in the drive, where passengers sampled a broad set of regions and moved between them in a less predictable manner; it was lowest during the lane change, a brief maneuver in which the relevant information is confined to the road ahead and the adjacent lane. The scenarios differed simultaneously in visual complexity, in the presence of moving agents, and in duration, so the present data cannot isolate which feature drove the differences. Findings 2 and 3 are complementary rather than contradictory: gaze entropy captures how broadly fixations are dispersed and how predictable the transitions between regions are, not which regions were fixated. Interface modality therefore changed where passengers looked without changing the organization of their scanning, and within that structure the scene, rather than the interface, was the dominant influence. Essentially, passenger visual attention remained coupled to the driving environment even after the responsibility to drive had been removed.

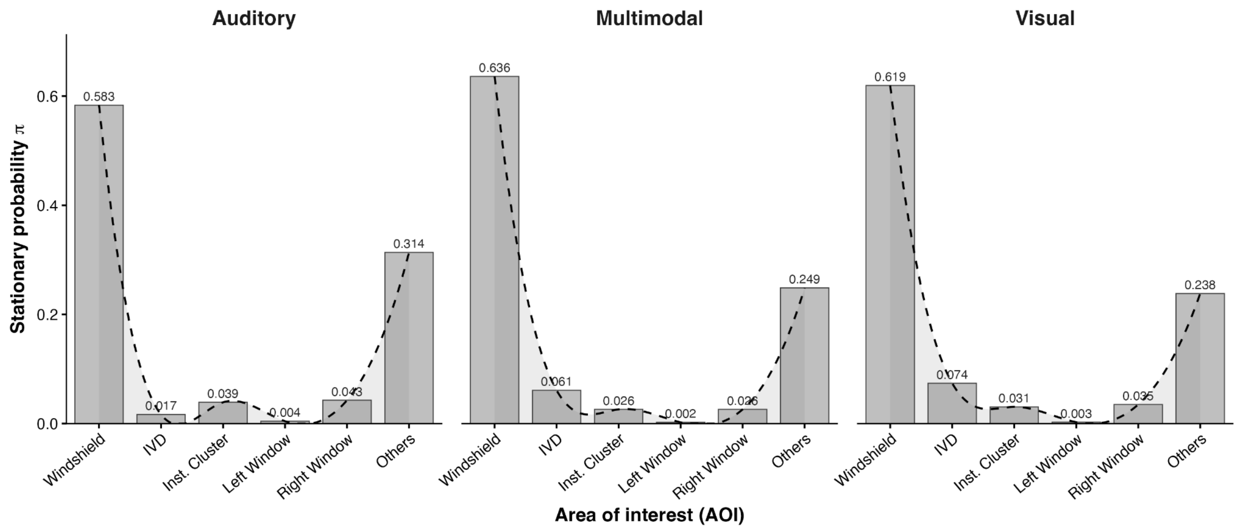


**Figure 3. Stationary gaze distribution by HMI modality.**

## Design Recommendations

Six recommendations for the design of passenger-facing in-vehicle HMI follow from these findings.

**1. Communicate intent and treat modality as secondary.** Trust increased significantly in all three conditions, so a channel that communicates what the vehicle perceives and intends should be the baseline requirement, regardless of modality.

**2. Pair channels rather than choosing between them.** The multimodal interface produced the highest trust and transparency with no penalty in workload or usability, and adding speech did not displace use of the visual display.

**3. Deliver intent before action.** All conditions used a five-second lead, in line with evidence that before-action explanations support trust and comprehension better than after-action.

**4. Displays locations should be readable with minimal deviation from the forward view.** Passengers anchored their scanning on the roadway, and participants themselves identified display placement as affecting how easily they could interpret the interface.

**5. Design for monitoring that declines as trust develops.** Higher trust was associated with less monitoring, so interfaces should support disengagement while allowing for easy re-engagement.

**6. Account for the physical presence of the display.** An inactive screen still attracted glances and appeared to displace attention toward the instrument cluster, indicating that a display is an attentional object even when it carries no information.

## Limitations and Future Research

Several limitations must be noted. The study was conducted in a driving simulator, which afforded the control and repeatability needed to compare scenarios and interfaces but cannot reproduce the consequences and variability of on-road travel. All participants were seated in the middle of the rear seat and travelled alone, a configuration chosen for consistency that does not represent the range of seating positions or shared rides possible in real life. The sample was drawn from a university population and was younger. The drive contained no automation failures, edge cases, or erratic behavior by other road users, a limitation participants themselves identified. One limitation warrants particular care in interpretation: because participants did not engage in non-driving-related tasks, the high proportion of attention at the forward roadway should be read as an upper bound on how much a L4 passenger would actually monitor the road.

These limitations show potential directions for further work. Extending the paradigm to on-road L4 vehicles would establish external validity. Permitting non-driving-related tasks would show how attention reallocates when passengers are free to disengage, which is the default state at L4 and the condition under which the multimodal advantage has been reported to weaken. Repeated or longitudinal exposure would test whether road-anchored monitoring decays as trust calibrates. Further work can also examine seating configurations and multi-passenger rides, adaptive interfaces that adjust modality, timing, and salience to the passenger's state, the communication of system limitations and uncertainty, and the effect of alert urgency and severity.

## Outcomes

This project was fundamental research, and its outcomes take the form of research outputs and the changes in design practice that those outputs enable rather than adopted regulation or policy.

The project delivered a reusable experimental capability in the form of an intent-communication interface developed in Unity and synchronized to a scripted L4 drive in a high-fidelity driving simulator, together with an instrumented paradigm for measuring rear-seat passenger response. As anticipated in the proposal, this capability is transferable to higher levels of automation and is positioned to inform interface design and evaluation for Level 5 people-movers. The project also delivered an evidence base with the systematic review which consolidates the literature on in-vehicle HMI and passenger trust at SAE L4 and 5, a body of work that had not previously been synthesized for the passenger, and the gaze analyses provide, to the authors' knowledge, the first characterization of the structure of rear-seat passenger visual scanning during L4 automation.

Research outputs include a systematic review submitted for peer review (Onyeukwu, Hungund, Shub, & Pradhan, under review); a paper on the design and evaluation of the in-vehicle HMI and its effect on passenger trust and system transparency; a paper on rear-seat passenger eye movements across interface modalities; and a Master of Science thesis in Industrial Engineering and Operations Research at the University of Massachusetts Amherst. The de-identified dataset generated by the project, comprising pre- and post-drive survey responses and gaze recordings from 36 participants, will be made publicly available through a data repository.

Dissemination and technology transfer activities include presentation at the NEUTC Symposium; engagement with the Association for the Advancement of Automotive Medicine; and incorporation of the project's methods and findings into courses taught by the principal investigator, including Human Factors Design Engineering and Automated Vehicle Systems. The project supported the development of two students: one doctoral student in Industrial Engineering and Operations Research, who was named a 2026 Lifesavers Traffic Safety Scholar, and one undergraduate student in Industrial Engineering.

## Impacts

The safety benefit of vehicle automation is realized only at scale, and scale depends on people being willing to ride. A majority of Americans currently report that they are not. Trust is the principal barrier, and the communication of vehicle intent is a direct and inexpensive lever on trust. This project provides evidence that any form of intent communication was associated with increased passenger trust after a single seven-minute exposure, and that redundant multimodal delivery was associated with the greatest increase in trust and in perceived transparency. Interface design is therefore a tractable point of intervention on a barrier that is otherwise addressed only slowly, through accumulated public experience. Set against approximately 40,000 annual roadway deaths in the United States, with driver-related factors identified as the critical reason in approximately 94% of crashes (NHTSA, 2018), accelerating the appropriate adoption of systems that remove the human from the driving task carries substantial safety benefit.

Any adoption should indeed be appropriate and not blind, and this work distinguishes these. Interfaces that make the vehicle's perception and intent clear support trust that tracks the system's actual capability, rather than trust extended blindly. The gaze results show passengers monitoring the roadway heavily on first exposure and adapting that monitoring to the demands of the scene, which is the behavioral signature of trust still being calibrated. Interfaces that keep passengers informed support calibrated reliance and reduce the risk of both disuse and overtrust.

The findings also bear on equitable mobility. Older adults and people with disabilities face barriers to conventional and shared transportation that automated services could reduce, and trustworthy passenger-facing communication is a precondition for those groups to benefit. The finding that an auditory-only interface performed comparably to a visual one on trust is directly relevant to passengers with visual impairment, and is consistent with prior work on interfaces designed for visually impaired users (Brinkley et al., 2019).

Finally, the results are transferable beyond the case studied here. The design principles identified, i.e., communicate perception and intent, deliver before the action, maintain consistency between display and behavior, and pair channels, apply to automated shuttles and people movers, to external interfaces intended for other road users, and to the design of occupant-state monitoring systems that take gaze as an input.

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