The XXXVIth Annual International Occupational Ergonomics and Safety Conference
Denver, Colorado
August 5-6, 2024

Low-Speed Automated Vehicles in Mixed Traffic: A Preliminary Model of Risk

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Abstract: High-level (Level 4/5) low-speed automated vehicles (LSAVs) are being developed and deployed on select traffic corridors due to their perceived safety benefits and potential impact on the first mile/last mile problem. Introducing LSAVs may reduce crash severity due to their low speeds and rapid response times due to relying on sensors instead of human perception, but it is unclear how crash risk throughout the local traffic system is affected when an LSAV is operating in mixed traffic with human drivers. We present qualitative data on interviews of experienced LSAV safety operators along with quantitative data on field observations comparing local traffic behavior (i.e., lane changing) around an LSAV and a typical passenger vehicle in Rochester, MN, USA. We supplement the data with a preliminary risk analysis using the Functional Resonance Analysis Method (FRAM) to examine potential patterns of risk and system variability when drivers follow and overtake an LSAV. The quantitative analysis of the lane-changing data indicates that drivers are more likely to change lanes around the LSAV during normal operations, compared to the human-driven passenger vehicle. The qualitative analysis of interview transcripts indicates that the operators remain critical components in ensuring local traffic safety and efficiency, strategically filling in the gaps unmet by the currently employed technology through monitoring the traffic situation, taking pre-emptive control of the automated vehicle in anticipation of problematic scenarios, and communicating with other nearby drivers to communicate intentions and negotiate traffic conflicts. The presented FRAM modified a published FRAM model for drivers overtaking another human driver, instead assuming that the overtaken vehicle was an LSAV, such as the observed LSAV in Rochester, MN. The analysis indicated that the LSAV with current operational parameters had reduced some sources of variability in the traffic system while other sources of performance variability increased, suggesting mixed benefits of LSAVs for risk in mixed traffic. Overall, the findings indicate that system designers and safety professionals should plan and account for unexpected secondary sources of risk if LSAVs are deployed at scale.

Keywords: autonomous vehicles, road safety, risk assessment, driver behavior

1. Low-Speed Automated Vehicles in Mixed Traffic: A Preliminary Model of Risk

Autonomous vehicles have the promise of making our roads safer and more efficient, as automation continues to take over lower-level control tasks (e.g., speed maintenance, lane-keeping) and has begun to take over higher-level tasks (Young & Stanton, 2023). However, machines cannot simply be a substitute for people, as system functioning, system dynamics, and how people perform given roles in complex systems are usually underspecified and poorly understood by technology designers, leading to unexpected and unintended consequences when implementing new technologies (Woods & Dekker, 2000). This is a problem that has long challenged the successful implementation of automation in aviation and naval operations (Sarter et al., 1997) and now challenges the implementation of automation in driving (Lee & Seppelt, 2012). Automation technologies change systems by changing the nature of feedback (e.g., cues, modes), the task structures within the system (e.g., algorithms different than human mental models, behavioral adaptation), as well as the relationships between actors (e.g., expectations, trust). For driving, automation represents a unique challenge, because not only is the driving environment visually and physically complex and requires the performance of multiple overlapping tasks, but unlike in most other domains, drivers are not specially trained in how to handle automated systems and represent a large population that spans a significant range of experience, age, goals, capabilities, and sociocultural background (Lee & Seppelt, 2012).

DOI: https://doi.org/10.47461/ISOES.2024.Kessler

Given that automation has only begun to take over higher-level driving tasks (e.g., Level 3 automation), it will be some time before fully automated (e.g., Level 4 and 5) vehicles are a significant presence on the road, giving safety professionals and those involved in risk management time to evaluate the effects that fully automated vehicles may have on the roads in significant volume. Currently, the initial exposure drivers will have to a fully automated vehicle will likely be automated shuttles. As of 2023, there have been over 30 pilot programs for connected and automated shuttles in Europe (Chaalal et al., 2023), and as of 2021 at least 17 pilot projects for low-speed connected and automated shuttles in the United States, with more underway (Coyner et al., 2021; Hague & Brakewood, 2020). Automated shuttles are of particular interest because they promise better accessibility to the transportation network for those who need it, thereby improving equity and sustainability, while providing an avenue to address the first-mile last-mile problem (Chaalal et al., 2023). The piloting and deployment of automated shuttles, particularly their low-speed iterations in mixed-traffic environments, allows for the examination of incidents of fully automated vehicles interacting with the traffic system and the corresponding unexpected and unintended consequences of implementing these technologies to better prepare for and mitigate risks of other types of automated vehicles (e.g., passenger vehicles). Currently, risk assessment for fully automated vehicles has primarily used simulation modeling and prospective accident analysis (Garg & Bouroche, 2023). These more speculative approaches are valuable, but no substitute for direct examination of the system in the world, as nature is far greater than the imagination of humans (Feynman, 1955). With multiple methods, we assess the risks of fully automated vehicles within mixed traffic, specifically low-speed automated vehicles (LSAV), given the availability of real-world deployment data with LSAVs.

1.1 Automated Shuttles and Risk

Low-speed automated shuttles have been modeled as improving safety while reducing efficiency in mixed-traffic scenarios (Garg & Boroche, 2023). However, there are hazardous circumstances that occur more frequently with LSAVs present. Drivers were reportedly frustrated at the slow speed of LSAVs in pilot deployments (Nesheli, et al., 2021) and there were greater rates of close car-following behind an LSAV (Wen et al., 2022). There are correspondingly greater rates of rear-end and sideswipe crashes for LSAVs relative to human-driven vehicles (Houseal et al., 2022; Zhu & Meng, 2022). An impatient driver may attempt to change lanes and overtake the LSAV, and drivers that attempt to overtake a slow or stopped lead vehicle may take their eyes off the road ahead to view the adjacent lane, leading to more sideswipe and rear-end crashes (Muttart et al., 2021). Drivers may also have incorrect expectancies for automated vehicles such as LSAVs (NTSB, 2019). When a car-following driver is expecting the lead vehicle to match the overall speed of traffic and is momentarily distracted, this could lead to a rear-end crash if the lead vehicle is an LSAV on a street with higher average traffic speeds. Another example of an unmet expectancy includes the anticipation that drivers of lead vehicles will turn right-on-red (if this maneuver is legal), with potential frustration and risk-taking on the part of following drivers when this expectancy is not met if the LSAV is programmed to not turn right-on-red.

LSAVs behaving in unexpected ways, such as not turning at an intersection on a red light when legal, is one example of a potential source of risk of automated vehicles that is not a direct consequence of the low speeds of the vehicle. Another source of risk that is not directly associated with low vehicle speeds is ambiguous feedback to other nearby drivers. Because new technology responds differently to human expectations, additional communication is needed at least during the initial deployment periods (Mirnig et al., 2022). A survey of eHMI designs has found that the designs have been targeted towards pedestrians and cyclists, with only a minority of eHMIs intended for vehicle-to-vehicle communication (Dey et al., 2020). The content of the eHMI messages toward pedestrians mirror the content of the communication dynamics between drivers and pedestrians. The eHMI for pedestrians uses icons, text, or abstract symbols to communicate stopping or yielding (Dey et al., 2020), whereas human drivers communicate by eye contact, hand gestures of the friendly variety, and flashing their lights to indicate stopping or yielding (Sucha et al., 2017). However, there are several communication channels and strategies between drivers, including the use of signals and hand gestures to indicate intentions, commands, or social etiquette (Renge, 2000). Having eHMI fulfill this role has not been a focus of research, outside of some preliminary work considering eHMI's role in reducing conflicts at intersections, close following, and overtaking (MS1 and MS2 in Mirnig et al., 2022).

1.2 Med City Mover Project

The Med City Mover (MCM) project was an LSAV demonstration in downtown Rochester, MN, USA, during 2021-2022. It comprised of two 6-person LSAV shuttles manufactured by EasyMile and operated by First Transit. The shuttles navigated an approximately 1.3 mi (~2 km) rectangular loop around the business district, residential neighborhoods, as well as the Mayo Clinic. The shuttles either progressed straight or made right turns at intersections to complete the route, which included two stops to pick up and drop off passengers. The shuttles always had a safety attendant/operator aboard. The street was shared by other traffic, including passenger vehicles, buses, human-driven shuttles, cyclists, and pedestrians. The speed limit on all roads was 25 mph (~40 km/h), and represented a variety of street types, including 2-lane roads, one-way roads, and 4-lane roads. The MCM shuttles operated at roughly10-12 mph (16 km/h) and took roughly 25 minutes to complete one loop of the route. The stated intention of the MCM project was to demonstrate the feasibility of automated shuttles to the public via engagement, test the technology's performance, and identify needed infrastructure changes to the roadways to operate similar vehicles safely (MnDOT, n.d.). The research team investigated the propensity for risky behavior by other drivers around the MCM while the MCM was in operation, particularly lane changing of nearby drivers.

1.3 The Present Study

The investigation of risk imposed by these LSAVs used multiple methodologies. The first was a field study examining the rate of lane changes by nearby drivers around the MCM shuttles when in operation, relative to the rate of incidents around a human-driven passenger vehicle. The second was a series of qualitative semi-structured interviews with safety attendants of the MCM shuttles and similar deployments or their trainers and managers. Finally, based on the interviews and the field observations, the research team modeled risk from this iteration of the LSAV using a previously constructed FRAM for driver overtaking of a lead vehicle (Hollnagel, 2017).

2. Method

2.1 Quantitative Field Observations

A research team member boarded an MCM shuttle that was on its rectangular route around downtown Rochester. For comparison, a member of the research team also boarded a researcher vehicle (e.g., a passenger car or SUV) that drove the same route as the MCM shuttles. While on the MCM shuttle, the researcher recorded the behavior of vehicles around the shuttle, including vehicles that would change lanes from behind the shuttle or change lanes to cut in front of the shuttle, or both. The same measures were taken when the researcher boarded the passenger vehicle, driven by another member of the research team. These counts were aggregated into a single lane change measure, one for the MCM shuttle, and one for the human-driven researcher vehicle. The research team collected driver behavior counts for 46 total loops onboard an MCM shuttle and 48 total loops onboard the researcher vehicle, across a four-month period from May 2022 through August 2022.

2.2 Qualitative Interviews

The research team interviewed 6 individuals. Three of the 6 had previous experience as safety operators of automated vehicles like the MCM, and 3 of the 6 interviewees had experience being a safety attendant on the MCM shuttle. Interviews were conducted via videoconference to take advantage of transcription software and ease of access to the participants. The interviews were conducted in a semi-structured format with 19 prepared questions covering general experience questions, training, shuttle operation, and safety, interactions with other drivers, and multimodal safety questions focused on pedestrians. Interviews typically took approximately an hour to complete.

Interview transcripts were coded using grounded theory, in which insights and codes were developed as part of the coding process. After agreeing upon an initial codebook, consisting of 70+ unique codes, two researchers independently coded the remaining interviews with Taguette software (Rampin R & Rampin V., 2021). Additional codes were added over the course of the coding when needed, and coding ended once an interview resulted in few new codes (i.e., 5% new), indicating saturation. An analysis indicated good agreement between coders. Researchers then developed higher level "axial" code groupings.

2.3 The FRAM Risk Assessment

The research team borrowed from a published FRAM model analyzing the patterns of performance variability between a human-driven vehicle overtaking a lead vehicle and an automated vehicle overtaking a lead vehicle (Grabbe et al., 2022). Given the present emphasis on lane changing and overtaking by other vehicles, the published FRAM model by Grabbe and colleagues (2022) was slightly modified to remove a subset of the functions in their instantiated model, focusing only on a four-lane road with the presence of a lead vehicle and a following vehicle. Instead of asking about the performance variability when the following vehicle is automated, the modified model considered the performance variability that arises

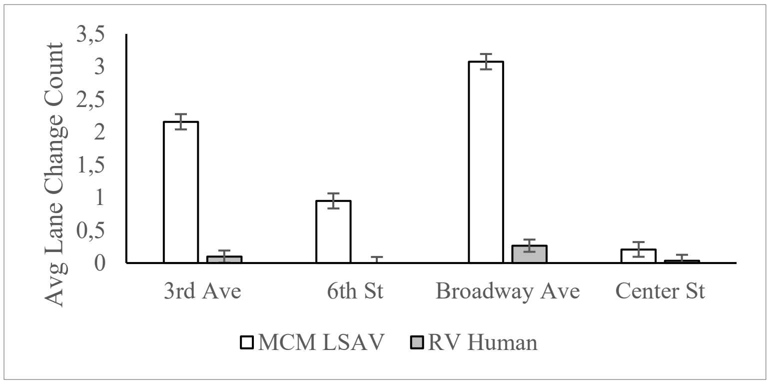

Figure 1. Average lane change count by observation period around the observed vehicles per location. Error bars are SE.

when the lead vehicle is an LSAV. Otherwise, the functions and aspects of the functions remained consistent with the previous model. On the simplified and modified FRAM model, the research team determined whether each function was carried out by a human, machine, or organization, generated the sources of internal and external variability for each function and then allowing for couplings between the functions implied by the scenario description. With the couplings established, the team described the potential functional coupling variability between functions (Hollnagel, 2017).

3. Results

3.1 Quantitative Field Observations

The coded count data was analyzed with a Vehicle Type (MCM, RV) by Time of Day (Early Morning, Late Morning, Lunch, Early Afternoon, Late Afternoon) by Location (3rd Ave., 6th St., Broadway Ave., Center St.), Between-Subjects ANOVA, a 2 x 5 x 4 design. The only significant effect was a Vehicle Type x Location interaction, $F(3, 15.6) = 10.27$, $p = .001$, $\eta_p^2 = .664$. A post hoc analysis found that the number of observed lane changes around the vehicle in question significantly differed depending on location. There were significantly more average lane changes around the MCM LSAV compared to lane changes around the human-driven researcher vehicle for 3rd Ave (2.16 vs. 0.98, $p < .001$), 6th St (0.95 vs. 0.00, $p = .001$), Broadway Ave (3.08 vs. 0.265, $p < .001$), but not for Center St (.21 vs. .03, $p = .549$). Center Street at the time of observation was a two-lane road with relatively high traffic density for similar road types. The other three locations were multiple-lane roadways allowing for more than one lane of traffic for a direction of travel. See Figure 1.

3.2 Qualitative Interviews

The analysis of the qualitative interview coding produced a significant number of axial codes, each describing a different challenge or phenomenon encountered by LSAVs. These codes pertained to interactions from other road users, safety measures/systems, technical difficulties of LSAVs, and safety operator strategies, procedures, and protocols. A subset of the major axial codes can be viewed in Table 1.

Table 1. Subset of Major Axial Codes from LSAV Operator/Attendant Interviews

Operators take over and manually stop further away from crossing pedestrians	The LSAV does not drive like a normal car, leading to disruptions and frustration	Operators interact with others outside the LSAV to communicate intentions
LSAV behavior designed on legal traffic behavior and encounters issues when humans break traffic rules	Objects marginally in the lane of travel (construction, parked cars) forced operators to manually drive around	During periods of heavy traffic, the LSAV was occasionally taken off the road due to the potential traffic disruption
Operators do pre-trips/test runs as a procedural part of a workday	Other drivers often pass and overtake recklessly due to the LSAV's slow speeds	Drivers do not understand how the LSAV "thinks"

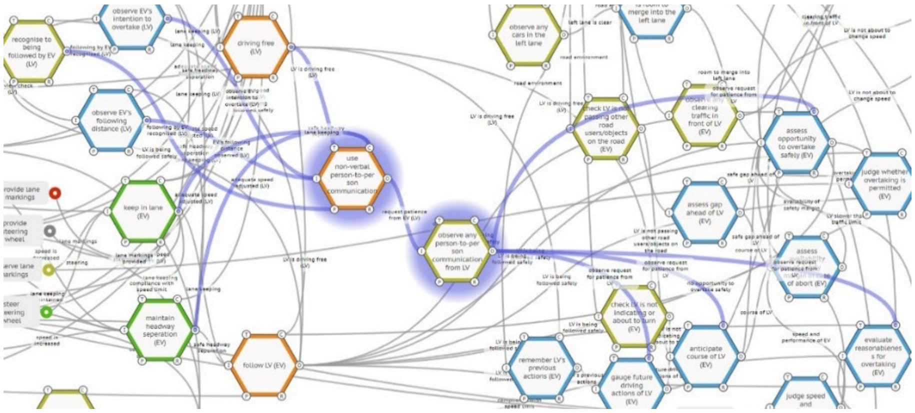

Figure 2. FRAM functions for communication between vehicles and their connections highlighted.

3.3 The FRAM Risk Assessment

Preliminary FRAM analysis found that 23 of the 73 total functions had an atypical variability for its function type, indicating that these functions had a potentially higher rate of disruption. A pair of functions were identified contributing a disproportionate amount of influence within the system: "use non-verbal person-to-person communication (lead vehicle)" and "observe any person-to-person communication from lead vehicle," highlighted in Figure 2. This interaction these functions represent is integral to the outcome of the scenario in this model, with many upstream functions having atypical variability, and many downstream functions relying on the output of this pair.

4. Discussion

While the technological safety measures in place ensure that the LSAV itself rarely crashes into anything, the inflexibility of the system often affects surrounding traffic in a disruptive manner. The lane-changing data demonstrates that drivers are more likely to change lanes around the LSAV during normal driving, compared to a human-driven passenger vehicle, indicating the magnitude of the agitation felt by surrounding drivers. The interview data indicates the operators aboard the MCM were regularly able to intervene in challenging situations, strategically filling gaps unmet by the automation by monitoring traffic and the route, taking pre-emptive control of the automated vehicle in anticipation of problematic scenarios, and communicating with other nearby drivers to communicate intentions and negotiate traffic conflicts.

The FRAM analysis indicated that the LSAV with current operational parameters reduced some sources of variability in the traffic system by converting some roles normally occupied by humans into functions performed by technology. However, consistent with the interview data, the FRAM model demonstrated the value of human operators/attendants. Human-to-human communication with the following vehicle was modeled with significant performance variability, with many upstream functions influencing the output, and many downstream functions being influenced by that output. This suggests that these communicative functions have the potential for significant functional resonance within this system (Hollnagel, 2017). Effective communication provides an opportunity for operators to calm traffic around the LSAV, potentially reducing the risk of aggressive overtaking. Thanks to the large windows in the MCM, operators can engage directly with other drivers through hand signals and facial expressions and partially explain the LSAV's situation.

LSAV operators were able to dampen the disruptions the LSAVs otherwise would have had on the traffic system by adjusting or adding to their operating procedure. Humans can adjust their performance to changing situations, unlike most technology, and adopt this necessary communicative role. Companies would like to remove these onboard attendants altogether, but they should not do so until they have developed an adequate eHMI repertoire for vehicle-to-driver communication, as most efforts in eHMI development has focused only on vehicle-to-pedestrian messaging (Dey et al., 2020)

Overall, the findings indicate that system designers and safety professionals should plan and account for unexpected secondary sources of risk if LSAVs are deployed at a significant scale, with a combination of low-severity accidents directly involving an LSAV and infrequent, high-severity accidents indirectly involving an LSAV, due to disruptive effects on traffic.

The operator's ability to intervene and assist the LSAV when needed, managing situations that would otherwise be disruptive to the surrounding mixed traffic remains valuable to system functioning and cannot yet be easily replaced with eHMI.

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