Simulated Extreme Experiential Training for Engaging with Automation

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Abstract

As Advanced Driver Assistance Systems (ADAS) become more widespread and capable, enhancing road vehicle safety and performance, drivers will increasingly encounter situations where system abilities are unclear, human/machine roles are not well defined, and human performance may demand augmentation. How might experiential training help drivers to learn the capabilities and limits of an unfamiliar ADAS, and what level of intensity is required for effective training transfer? In the manner that trust-building exercises (like the 'trust fall' from a picnic table into teammates' arms) calibrate human-human trust, can experiential training in 'edge-case' and extreme driving conditions scenarios be delivered through simulation to drivers, providing training on an unfamiliar ADAS, such that they build an accurate mental model of their vehicle's capabilities and limits, and of their own?

Keywords [1]

training, simulation, VR, experiential training

1. Introduction

Automated, autonomous, and artificially-intelligent (A^3) systems [14] are increasingly being integrated into road vehicles sold to members of the public [4]. Without an understanding of the behavior of the A^3 systems in their vehicle, drivers may suffer an "automation surprise" [13] and adverse automated system behavior [5], either due to the failure of the system, or as a result of being unprepared for system actions—irrespective of whether those actions are correct or incorrect responses to environmental conditions or driver behavior. Training can provide drivers with a more accurate mental model of the system [9,10,15] and its responses to various road conditions, and thus allow drivers to better expect its behavior and to work with the system rather than against it. As was noted by Farmer et al. [2], drivers who were unfamiliar with antilock braking systems did not properly take advantage of the safety benefits afforded, and in some cases inadvertently defeated the system when surprised by its behavior, causing crashes or increasing their severity. More advanced systems that can do far more than mitigate a skid or brake in response to an imminent forward collision enhance safety and driving performance–but only if drivers appropriately trust the vehicle's automated systems and their own driving abilities. Misuse and abuse of automated systems [11], and poor correspondence between the driver's mental model of the system and the reality of its limits could increase crashes, especially in situations of human-system conflict. If drivers are surprised by the actions of the system, they may wrestle with it, even if the system is acting correctly, increasing risks; likewise, they need to know when the system will fail or err and thus when to act against it. Experiential training can ameliorate this problem by teaching drivers when to trust the system, and when to fight it [7].

Training using simulation has a long history in aviation [6], and flight training often includes exposure to both routine and emergency situations. Providing drivers firsthand experience with how their vehicle will behave in extreme situations, such as on an icy road surface or a near-collision situation, how automated features will enhance their driving capabilities, and how automation will act to protect the driver and others in rare situations (edge cases), should improve correspondence between the driver's mental model of the system and reality–and allow the driver to better use the system to enhance safety. And such experiences can also provide the driver insight into how they will behave in

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such situations and what their own capabilities and limits are. Driving simulation is now both realistic enough and inexpensive enough to be deployed widely to both university research labs and to locales such as automobile dealerships, enabling drivers to experience otherwise rare and dangerous situations with perfect safety, and with computer-based coaching available, see Figure 1.

Figure 1: A high-presence driving simulator can be used to provide a training experience, or can be used to test the effects of experiential training.

2. Training Drivers with Simulated Extreme and Edge-Case Driving Situations

To examine the efficacy of training drivers using virtual reality simulation, and to assess the benefit of providing drivers with experiential training including extreme and edge-case situations, a two-stage study can be employed with a training phase followed by a testing phase. The initial training experience, which includes either only routine situations or a combination of routine and extreme situations will be followed by a testing experience that includes both routine and extreme situations, and to study training transfer, situations that have been encountered in training as well as novel situations similar but not identical to those seen in the training, see Table 1 and Figure 2.

Table 1
Experimental Conditions

	Training Stage	Testing Stage
Routine Situation Training	Explicit training in ADAS capabilities under normal conditions.	Assessment of driving with ADAS in normal and extreme situations
Routine + Extreme Situation Training	Explicit training in ADAS capabilities under normal and extreme situations.	Assessment of driving with ADAS in normal and extreme situations

Following the training stage, participants will be provided with a questionnaire interrogating their understanding of the ADAS capabilities and limits, and their expectations of what it will do in situations they encountered in the training, and in novel situations to gauge their understanding of how the ADAS will function in situations which they did not encounter. This questionnaire set will also evaluate the participants' self-reported trust in the ADAS, and this reported trust will be compared with their driving behavior in the simulated driving experiences–where they may demonstrate trust or distrust of the system through reliance behaviors. Participants' mental model of the system, and that model's correspondence with the actual capabilities and limits of the system will be assessed through a mental model evaluation exercise, similar to the one developed by Rozenblit and Keil [12]. This technique combines interview and survey techniques to assess the depth of understanding on the part of the participant and how well that understanding matches the actual system design. Evaluation of driver behavior demonstrating reliance has been used previously in simulation research [3,8], and the research proposed will break new ground by further researching the interaction of trust and reliance.

We hypothesize that training which exposes participants to a larger range of sample situations, specifically extreme conditions driving or edge-case situations, will help participants build a more accurate mental model of the system's capabilities and limits, and better calibrate their trust in the system.

- *Hypothesis 1:* Extreme situation and edge-case training will better calibrate trust in the ADAS, compared with training that only includes exposure to routine situations.
- *Hypothesis 2:* Extreme situation and edge case training will allow participants to build a more accurate mental model of the ADAS, compared with only routine situation training.

Participants will return for a second simulated driving experience after a delay of approximately one month. This delay allows for forgetting to occur, which allows for an assessment of long-term retention of what is learned in the training phase [1]. In the testing phase, all participants will be exposed to both routine and extreme driving situations. Driver behavior in these situations can thus be compared between participants who received both routine and extreme situation training and those who received only the routine situation training. Following the testing phase simulation experience, participants will again be provided with the questionnaire battery to assess their mental model of the ADAS and their self-reported trust in the system.

- *Hypothesis 3:* Extreme situation and edge case training in the training phase will help participants to perform better in extreme and edge case situations in the testing phase.
- *Hypothesis 4:* Extreme situation and edge case training in the training phase will help participants to perform better in routine situations encountered in the testing phase, due to greater training transfer.

The challenges presented will be comprised of varying weather (clear weather, fog, snow) and road conditions (dry road, wet road, ice), and a set of obstacles including pedestrians, bicyclists, animals, other vehicles, and obstructions such as rocks or debris. In addition, the training set will provide examples of the failure modes of the ADAS: both false positive and miss situations, and examples where the system acts to protect the driver from unseen hazards or threats that move faster than the driver can react–taking advantage of the superhuman abilities of technological systems. These challenges will provide a way to assess the participant driver's ability to respond to situations they have seen before, and those they have not, and thus assess training transfer to novel situations.

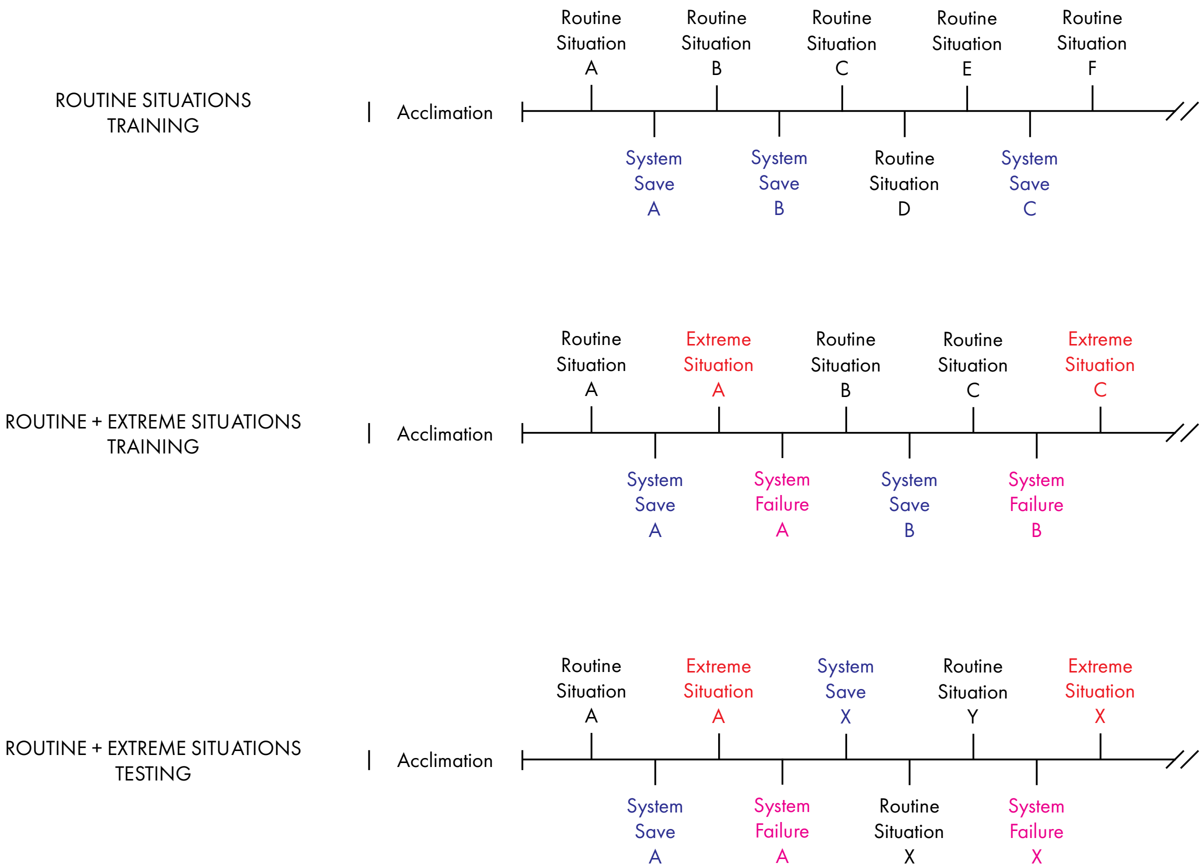

Figure 2: Outline of the training and testing event sequences as participants will experience them in simulation. Participants will be randomly assigned to experience either the routine or routine + extreme training program; all participants will subsequently experience the routine + extreme situations testing sequence. Situations presented in the training experiences are labeled A, B, C, etc. and situations presented to test transfer of training to novel situations are labeled X, Y, Z.

2.1. Aims of Investigating Extreme Experiential Training in Simulation

Studying training transfer from a lower fidelity and lower presence driving simulation (e.g. a limited field of view simulator or HMD-based simulation) to a higher fidelity driving simulation (as an analogue for the real road environment) will enhance the knowledge of how VR can be used for training members of the public. Where in the past, high-presence simulators have been quite expensive and limited in availability, the proliferation of VR and high-fidelity driving interface hardware makes it possible to deliver training in locales such as automotive dealerships, rental agencies, driving schools, and even in home environments. By investigating how training using VR persists over time and how learning can be generalized will have great value to other training-related areas in industry, as well as in the driving sphere [1,10]. Understanding how training on a limited set of examples transfers to similar but novel situations will expand the state of knowledge in education, training, HCI, and VR studies, in addition to enhancing driver safety.

As computer and robotic technologies have proliferated even in just the past few years into every area of modern life, the understanding of how people, especially non-specialists without an engineering or computing background, relate to technology needs to be updated. Measures of trust in technology, for example the inventory developed by Jian, Bisantz, and Drury and published in 2001 [9], may not fully encompass the relevant theoretical constructs, as noted by Hancock et al. [7]. To update the tools for measuring self-reported trust, we aim to develop more modern measures of trust in technology and technological agents specific to interaction with agentic systems [15] such as partially-automated vehicles. These survey measures of trust will be linked with behavioral measures of reliance, a related but not identical construct [2] through triangulation of methods. Reliance, which has been explored by

Lee and See [14], Miller et al. [16], and Fu et al. [4], relates to behavior, rather than the cognitive or theoretical construct of trust, and to this end it is necessary to measure, though driver behavior, the actions that demonstrate their level of trust in the system–and whether that trust and reliance is well founded, or is itself erroneous. This model of trust and reliance is likely constructed from a combination of trait factors and experience, as shown in Figure 3.

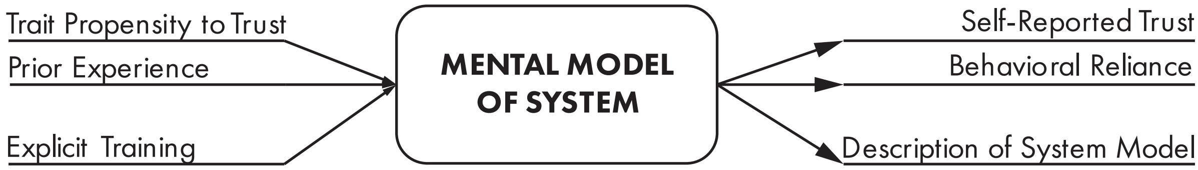

Figure 3: Trait propensity to trust, prior experience, and training influence the mental model one holds of a system. This mental model interacts determines self-reported trust as well as reliance behavior, and underpins their description of the system when queried.

Study of mental models of technology and how these mental models influence interaction behavior are even now more limited than the understanding of trust and reliance. While there has been research conducted on how training influences the development of mental models and their accuracy [13], and techniques have been investigated for studying correspondence between a user's mental model and that held by the designers of the technology [11,12,21], the area of mental models research deserves further attention. While distortion is inevitable in any research of this kind as it may be impossible to fully articulate one's mental model [20], and therefore comparing a user's and designer's models injects noise on both sides, it is still likely a valuable endeavor to investigate correspondence between mental models, and to assess the effectiveness of experiential training, in addition to other types of instruction, on increasing congruence of users' mental models with the reality of the system.

Transfer of learning from the training phase to the testing phase will be assessed through measurement of driving behavior in the testing phase, where participants will be presented with both familiar and novel routine and extreme situations. It is hypothesized that participants who only experienced the routine situations in the training stage will have greater difficulty in the extreme situations presented in the second stage, compared with participants who received training including extreme situations in the training phase. Extreme situation training may improve performance in novel routine situations, as well as in extreme situations, as a result of greater experience in interacting with the ADAS and driving in challenging conditions.

3. Conclusions

This proposed course of study, exploring the value of experiential training for drivers encountering novel vehicle systems, will almost surely result in an expansion of the understanding of training transfer generalizable to other areas of human-technology interaction. Development of updated measures for trust and mechanisms for assessment of mental models, necessary for this endeavor will provide further benefits to researchers as well. Ultimately, this program of research will hopefully yield safety benefits to the driving public through the deployment of experiential training, provided the benefits prove material as forecast. If this study of training using VR to provide exposure to extreme and edge-cases in driving yields the anticipated results, and this type of training can be made widely available, driving safety may be substantially improved by giving drivers a way to learn about their vehicle's capabilities and limits, as well as to understand their own envelope of own abilities and limitations, and thus behave accordingly. Through this training they can better calibrate their trust in technological driving aids and in themselves, and as a result drive more safely, reducing the terrible toll of road incidents.

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5. References

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