The Impact of Autonomy-Enabled Vehicles and System Controls on Non-Users in Semi-Controlled Environments

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ABSTRACT

Commercial OEMs are fast realizing the long awaited dream of self-driving trucks and cars. The technology continues to improve with major implications for the Army. In the near tear, the impact may be most profound for military installations. Many believe, however, that the major limiting factor to wide-spread automated vehicle usage will not be technology but the human element. What happens when humans through no choice of their own are compelled to interact with self-driving vehicles? We propose a mixed-methods research study that examines the complex transportation system from both a technical and social perspective. This study will inform environmental controls (rules of the road and infrastructure modifications) and increase understanding of the social dynamics involved with vehicle acceptance. Findings may pave the way for a reduction in the over $400M the Army spends annually on non-tactical vehicles and the technical improvements, grounded in dual-use use cases will be directly applicable to warfighting scenarios.

INTRODUCTION

Early in the development of automated vehicles, research was necessarily of the foundational technical type required to develop working robots. This involved the development of means to accurately sense the environment and vehicle condition, process these inputs into commands or behaviours, and actuate a sub-system in the vehicle to perform the desired function [1]. Early robots and autonomous vehicles interfaced with humans more than interacted with them. Human-machine interaction (HMI) is an area of research involved in improving how the machine works with a human supervisor or operator [2]. As interaction has increased and autonomous systems are becoming viewed as team members more than mere tools [3]–[5] research today is emphasizing human-machine interaction which includes understanding intentions and developing shared mental models [2], [6], [7]. Again, this research is oriented on the machine working and interacting with the human operator, supervisor, or 'teammate'. The humans and the machine have a shared objective and the research emphasizes creating and making use of a shared mental model.

But what happens when humans who are not on the team are compelled to interact with the machines through no choice of their own as we might expect when human drivers pull up to a four-way stop to find other vehicles sans driver behind the wheel? How comfortable with they be? What will they expect? What will they do and how will early experiences shape follow-on behaviour? To date, there is little research investigating the impact of autonomy-enabled vehicles on non-users or, more importantly, the factors that influence non-user perceptions of autonomy-enabled vehicles.

The purpose of this study is to identify and characterize the factors that contribute to the social acceptance of autonomy-enabled vehicles. We will explore how and to what extent the environment can be adjusted to improve acceptance. "While engineers tend to be most interested in how products are made, what really counts is how they are used" [8, p. 7]. This study will inform policy and deployment strategies leading to better use of resources, safer deployment, and increased technology acceptance.

Military bases provide a unique opportunity to study the impact of autonomy-enabled vehicles on non-users[1]. Commercial companies are focused on improving technology to accommodate any and every circumstance.

[1] Recently, experiments by Google and the UK government have been announced which will attempt to learn more about the autonomous vehicles and their impact. Detailed information on specific research questions and research design are not currently available. See this article from IEEE and this article from the BBC for press release information.

Because transportation networks involving cars, trucks, bicycles, pedestrians, and everything else is a complex system, accommodating every eventuality is expensive and an unlikely route to a pragmatic solution. In addition to the uncountable number of scenarios, streets on the real world are full of people who are unlikely to ever again encounter the few automated vehicles being tested. Because these non-users will have a say in how quickly or whether these vehicles will be deployed at all – it is important to understand how accepting they will be and if conditions can be shaped to improve the likelihood of acceptance.

This study is important because non-users will have a say in how and whether self-driving vehicles become widely available. If too many non-user groups complain or lobby policymakers, deployment of these advanced systems will be delayed or thwarted altogether. Good solutions will fall victim to pursuit of perfect solutions and we will fall behind less litigious or less rigorous economies that benefit from learning by doing. Military bases allow for longitudinal study and access to non-users to understand how perceptions change over time. Policy changes are relatively easily controlled. The infrastructure can be adjusted. We propose a mixed method action-research study of non-user acceptance of autonomy-enabled vehicles on military installations. This study will inform policy and accelerate successful deployments of autonomy-enabled vehicles. Cost and risk in vehicle development will be reduced.

THEORETICAL FRAMEWORK

Traffic – both vehicular and pedestrian – are subject to ebbs and flows, or cascades, in which one small change, say a driver performing a panic-braking maneuver in response to being cut off on the highway, can have major consequences as drivers behind him hurriedly brake until you, four miles up the road, wonder what in name of all that is holy could be causing the slowdown. Vehicular and pedestrian traffic are complex systems [9]. They are made up of individual actors each ostensibly behaving in a self-maximizing manner inside a much larger network with relatively few boundary conditions and no central control, yet self-ordering generally prevails [10]. Complex systems are sometimes characterized by an inability to "force" them to behave a certain way from the top-down; they must be coaxed with subtle changes at the bottom [9].

System dynamics models are used to represent real-world situations with non-linear, emergent outcomes that occur primarily through feedback loops, like traffic [9], [11]. The outcomes as a result of input or process changes can result in what we colloquially refer to as "unforeseen consequences." Because system dynamics models are meant to simulate reality, which produces emergent outcomes, they are validated qualitatively based on the researchers' understanding of the world rather than formula by formula and algorithm by algorithm [11]. This social reality "is produced and maintained through situated action and is influenced by actors' histories, interests, environmental constraints, and power bases" [12, p. 1084]. System dynamics models often incorporate independent agents which can learn and adapt their behaviour with each iteration of the model [13]. Independent agents react dynamically within upper and lower boundaries which limit behaviours and responses to model stimuli [10], [13]. Variation to bounded behaviour is also incorporated at a set rate (e.g. 0.3% of the time the agent will behave in an entirely random manner and learn from the outcome based on the usefulness) [10]. This is the mutation rate. It is easy to see how models like this can be used to simulate real-world situations: think of the traffic on a small medical campus. There are pedestrians, parking lots, bi-directional traffic, intersections, loading and unloading, etc. People in this environment will generally follow the rules. An individual stopped at an intersection with no other cars will probably stay there for somewhere between 1.1 and 0.05 seconds. These are the upper and lower limits. But every now and again, the driver at the intersection will come to a rolling stop or use the pause to change the radio and stay longer. This is the mutation rate and assuming no accident occurs and the vehicle gets to its destination faster, it may perform the same behaviour next time because it learned this is a more efficient way to achieve the overall objective.

In the real world, an individual's conscious intention to perform a particular behavior strongly influences their successful performance of that behavior [14]. In other words, assuming they have the resources and physical means to do so, people are most likely to do something if they intend to do it. These intentions are, in turn, influenced primarily by three factors: their attitude toward the behavior – how they feel about doing it; relevant subjective norms – how they think other people feel about the behavior and the social pressure to do it or not; and finally, the amount of control an individual thinks they have over the behavior [14], [15]. A great deal of research has been done investigating the drivers of human behaviour from hedonic rewards and punishments, carrots and sticks, to more recent emphasis on high-order cognition [15]–[17]. This includes outcomes from earlier events that can shape attitudes, norms, and an individual's level of perceived control over future events [14]. An individual's motivation to perform a behavior can be carried from one instance to the next, like baggage. Perceived behavioural control is, in part, "people's perception of the ease or difficulty of performing the behavior of interest" [14, p. 183]. If we take for granted that the objective of people walking or driving toward a building is to enter the building their behaviour on the way there will be influenced by the ease or difficulty they have in transit, either while walking, driving, or parking.

We expect the theory of planned behavior to inform this research because in addition to the element of control, it accounts for individual perceptions of the social norms we expect will influence non-user attitudes toward autonomy-enabled vehicles. In the case of our research we can define outcome behaviour(s) as whatever accommodations or changes to baseline activities are required once autonomy-enabled vehicles are introduced. Will these changes be too burdensome on individuals to translate into broad, general acceptance? Will there be active resistance? To what extent or within what boundaries can social norms and normative behaviours be adjusted such that individuals are accommodating and not resistant? Finally, are there policy (rules of the road) or infrastructure adjustments that can facilitate acceptance?

Reciprocity is a fundamental social norm essential for cooperation [18], [19]. Reciprocity involves cooperating with others and sanctioning non-cooperators. When the threat of sanctions is removed, people tend to act in self-interested, utility-maximizing ways [19]. We expect that how or whether people reciprocate when interacting with vehicles not driven by human beings will be a critical element of this study. Will non-users display 'algorithm aversion' [20] and judge mistakes or close calls on the part of an autonomy-enabled vehicle more harshly than a similar human situation? If they have complete confidence in the technology will they disregard current traffic rules knowing the autonomy-enabled vehicle will not hit them? Again, what can policy (rules of the road) and infrastructure do to mitigate this?

Like the TPB, the Technology Acceptance Models (TAM and TAM2) are adaptations of the Theory of Reasoned Action [21]. The TAM posits that a person's perceived usefulness of a technology and its perceived ease of use are the primary factors that shape an individual's intention to use a technology and ultimately lead to either their actual use or disuse of a tool or system [22]. The technology acceptance model has its roots from the 1970's and early 1980's research involving user likelihood of adopting an information system based on its impact on their job performance. The model also borrows elements from research on the impact of self-efficacy on behaviour, decision-making theory, and the adoption of innovation [23].

Davis found that, while both a potential user's perception of a technology's usefulness and ease of use are strong predictors of a person's intention to use a system, perceived usefulness is significantly more strongly correlated with actual usage (Davis, 1989). Later Venkatesh and Davis (2000) dove deeper into the concept of perceived usefulness in follow-up research of TAM. This research produced an extension to the technology acceptance model in the form of TAM 2 which further leverages elements of the theory of planned behaviour by including additional independent variables such as subjective norms among others (Venkatesh & Davis, 2000). Importantly, Venkatesh and Davis found that, "people form perceived usefulness judgments in part by cognitively comparing what a system is capable of doing with what they need to get done in their job" (2000, p. 190).

The role of robots, including autonomous vehicles, is beginning to be viewed less as that of a tool used to perform a task and more as a collaborative team-member working side-by-side with humans [6]. Yanco and Drury ([24] outlined a taxonomy of six categories to describe human and robot interaction including the autonomy level of the robot relative to the amount of human intervention required; the ratio of robots to humans2; and the decision support mechanisms available to human controllers3. Additionally, much work is being done in man-machine teaming and human-robot interaction (e.g. Awais & Henrich, 2010, 2013; Francois, Polani, & Dautenhahn, 2008; Lebiere, Jentsch, & Ososky, 2013; Ososky et al., 2012; Woods, Tittle, Feil, & Roesler, 2004). This work and the taxonomy emphasize coordinated action and imply a common and commonly understood objective.

Researchers have identified a similarity between the relationship that humans have with robots in these teaming situations to the relationship between caregivers and children such as parent-child relationships or babysitter-child relationships [26], [27]. Much like in caregiving situations, robots are subordinate to the authority figure, but capable of independent 'thought' and action. Power dynamics are important in both of these relationships and may help us understand how non-users accept or reject the introduction of autonomy-enabled vehicles into everyday situations. In parent-child relationships where caregivers (either parents or babysitters) perceive themselves with low power and children with high power the caregiver tends to display negative attitudes and behaviours, even abuse, toward the child in situations where desired outcomes are not obtained [28]. In other words, if the person supposed to be in charge feels thwarted in achieving some desired end state due to the action of an actor who should defer to their judgment but is perceived to be beyond their control, they act out in negative ways. The Parent Attribution Test has been used to evaluate individual perceived impact on the outcome behaviours of

[2] Yanco and Drury [24, p. 6] describe eight ratios of human-to-robot each requiring various levels of autonomy. The eight types are: one human, one robot; one human, robot team; one human, multiple robots; human team, one robot; multiple humans, one robot; human team, robot team; human team, multiple robots; and multiple humans, robot team.

[3] The remaining three categories in Yanco and Drury's taxonomy [24] include: the criticality of completing a task successfully, which also encompasses negative outcomes if an error occurs; a time and space factor which addresses the physical location of the robots and humans and the latency with which behaviours and decisions interact; and finally the composition of the team of robots insofar as they are of a single type or a heterogeneous group.

robots based on the relative locus of control and balance of power in failure situations. An adapted version of this assessment tool may be useful in understanding causality of negative action on the part of non-users.

Research on man-machine teaming is exploring the importance of a robot's ability to express affect to improve communication and interaction with humans in complex environments [27], [29]. Ellis, et. al. [27] found that robots with arms are legs in a humanoid shape elicit higher scores of positive mood than those with wheels or tracks in the performance of tasks. Human tendencies to imbue anthropomorphic qualities on inanimate objects even extend to cars; vehicles with widely-spaced headlights are perceived as 'friendlier' than those with narrowly spaced lights. The design of a robotic system has a lot to do with how people perceive its ability to perform a task. A system designed to encourage positive affect will be perceived as being more effective than one that produces less positive affect [27], [29].

Ongoing research in man-machine teaming will inform our study, especially in areas where a shared goal is easily understood by non-users. Our research will complement this area of study because, unlike situations in which humans and machines are working together on a team, traffic situations, parking lots, and pedestrian walkways produce a complex environment with numerous agents who may not necessarily share a common or commonly understood objective. In fact perceived objectives, especially in the short-term may be at odds (e.g. "I am late for an appointment. I don't care if I cut you off or if I run across a parking lot").

RESEARCH QUESTIONS

Non-users, especially non-user groups, will have a say in how and whether autonomy-enabled vehicles are broadly deployed in the United States. We believe policy and properly organized infrastructure (environmental controls) can positively influence non-user acceptance of automated vehicles allowing researchers and developers to learn from good solutions now and develop better solutions faster. To understand how best to deploy autonomy-enabled vehicles and shape non-user attitudes we need to ask:

What factors contribute to non-user acceptance of autonomy-enabled systems in semi-controlled, campus-like settings?

How and to what extent do infrastructure and policy (rules of the road) changes influence non-user behaviours?

How do non-user perceptions of autonomy-enabled systems differ from extant transportation systems?

How and to what extent do non-user perceptions differ from observed behaviour?

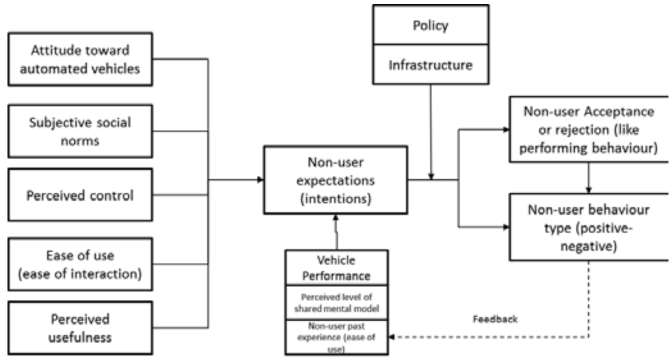

Figure 1: Draft Conceptual Model.

RESEARCH METHODOLOGY

Based on our mix of research questions that lend themselves to qualitative and quantitative inquiry, we propose a mixed method approach. Mixed methods research integrates qualitative and quantitative data enabling a more complete understanding of the problem under investigation [30]. Our approach will be framed in multiple, sequential studies with interventions based on the findings of earlier research phases. The multi-phase design lends itself to the evaluation of specific changes and helps us understand system impact and adaptations [30]. The initial case will consist of convergent parallel strands followed by an intervention at the research site. The convergent collection and analysis of quantitative and qualitative data will allow the researchers to "obtain different but complementary data on the same topic" (Morse, 1991, p. 122 from Creswell & Plano Clark, 2011). In our case triangulating observed non-user behaviour as they interact with autonomy-enabled vehicles (quantitative) with their perceptions and expectations of their interactions (qualitative) will provide a fuller understanding of what and how non-user motivations and behaviours are shaped.

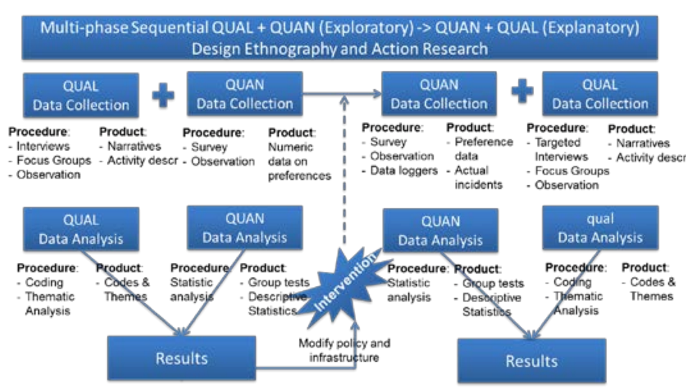

Figure 2: Research Plan Diagram.

Sample

Our sampling will be purposive [31]. This means our sample will not be random, but targeted. This approach enables us to focus on the geographic area and the infrastructure elements within it. Specifically, we will be able to gauge non-user reactions and measure behaviour over time. Staff members will, presumably, have the most frequent and consistent exposure to the automated vehicle. Family members visiting with patients or accompanying them to appointments are expected to have much less frequent interaction. Because we are interested in the bottom-up impact on the overall system, we are interested in the effect policy will have on behaviour and what this does to the overall efficacy of the systems. We expect the relative amount of influence will vary across our general non-user categories.

The initial phase of our study will include the staff, patients, and family members at a large military medical center. The medical center and barracks facility form a self-contained campus bounded by high-trafficked roads. Traffic within the campus, for the most part, consists only of the aforementioned targeted study participants. The commanding officer of the medical center and commanding officer of the barracks facility are supportive of the research. Following the intervention, we will observe and survey participants in the same area and group them similarly. Some of the subjects in these groups, by definition, will be the same subjects from the earlier phase. Our final qualitative study, which will help explain our quantitative data, will also group participants in this manner. Demographic questions regarding the individual's purpose for being in the area and frequency with which they visit the area will collected.

Results Integration

Unique to mixed methods research is the requirement to combine the various strands of research. There are two key points where data is combined. The first point interface is the time in the research study when the two strands of research are combined during analysis. The second is during the description of the research results [32]. Each point of interface has to overcome challenges to quality – data quality during the analysis stage and inference quality during the results stage [31]. Sound methodology and careful data collection can help to overcome the first challenge. The second will be addressed through the careful consideration of input from all of the research team members, their experiences, and the literature.

Our initial qualitative strand will leverage a grounded theory approach based on individual interviews and targeted focus groups. This allows us to incorporate the "social, historical, local, and interactional context" [33, p. 180] of the research participants' lived experiences into a more general understanding of system in which they live and work. Grounded theory involves the constant comparison of data, meaning the language used by research participants will be continually described, categorized, and coded while being compared against a conceptualization of the phenomena [34]. Researchers will be sure to record the intonation and pauses and use of humor and sarcasm during our interviews and focus groups which may provide insight to some buried or sub-conscious anxiety about interacting with autonomy-enabled vehicles. Subtle physical clues such as deferring to particular research participants may also reveal a social leadership structure very different from the labels or rank of individuals. This may be important with regard to how our research subjects understand and shape the social norms associated with regard to acceptance of these vehicles. Certain positions may have outsized influence in shaping the social norms of the people who interact routinely with these vehicles [35].

Our quantitative data will be collected through observation of non-users interacting with autonomy-enabled vehicles in the environment under stud. Observational data will be complemented by a short survey (to be designed) for willing participants. Observational data of behaviour such as making a turn across traffic, stopping at a four-way stop, and negotiating obstacles in a parking lot will be easily recognizable as generalizable to many traffic situations. Triangulation is the comparison of findings acquired using different methods, namely quantitative and qualitative, to discover which findings complement or conflict with one another or may not be present in a particular type of inquiry [36]. To triangulate the findings from our data we will compare non-user perceptions to actual behaviour. Outcomes from phase 1 will inform policy and infrastructure modifications for the intervention. Outcomes from phase 2 will help us evaluate the efficacy of the changes made during the intervention. The resulting analysis will facilitate a targeted list of policy and infrastructure modifications allowing for accelerated deployment of autonomy-enabled vehicles while reducing cost.

CONCLUSION AND NEXT STEPS

Once we understand the motivations and preferences of non-user populations we can model dynamic, learning interaction between non-users and autonomy-enabled vehicles and adjust environmental conditions and rules governing behaviour. Modifications to policy and infrastructure can influence efficient interaction and positive shape non-user acceptance of autonomy-enabled vehicles. This study's strengths are also its limitations: having a relatively controllable environment and population to study may limit its generalizability. Breaking the system into discreet, easily recognizable situations (e.g. “four-way stop” or “pedestrian crosswalk”) will mitigate this limitation.

This study will characterize non-user behaviour and the factors that shape their perceptions of these vehicles in situations familiar to any driver or pedestrian in typical urban transportation scenarios. Our next steps are to develop the survey instruments and baseline behavioural patterns, by group, in the environment we will be studying. Our schedule will be developed and overlaid against the ARIBO pilot project at Ft. Bragg, NC.

Having a better understanding of these factors and the impact of policy and infrastructure will accelerate the introduction of autonomy-enabled vehicles and improve overall system performance. Deployment costs will be reduced because good technology will be safe and acceptable instead of endlessly pursuing perfect technology.

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