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Computational models of cognition for human-automated vehicle interaction: State-of-the-art and future directions

ABSTRACT

We discuss the state-of-the-art and future directions of the development, evaluation, and application of computational cognitive models for human-automated vehicle interaction. The capabilities of automated vehicles are rapidly increasing and changing human interaction with and around the vehicle. Yet, at the same time, fully automated vehicles that do not require human interaction are not available. Therefore, systems are needed in which the human and the vehicle interact together. We discuss how computational cognitive models that can describe, predict, and/or anticipate human behavior and thought can play a crucial role in this regard. Such research comes from many different disciplines including cognitive science, human-computer interaction, human factors, transportation research, and artificial intelligence. This special issue brings together state-of-the-art research from these fields. We identify four broader directions for future research: (1) to continue Allen Newell's research agenda for cognitive modeling, but now apply it to the field of human-automated vehicle interaction; (2) to move from isolated theory-slicing to integrated theories, (3) to consider cognitive models both for analysis of interaction and for use in embedded systems; (4) to move from models that mostly describe to models that can predict.

1. Introduction and State-of-the-Art

The capabilities of automated vehicles are rapidly increasing, and are changing interactions in traffic considerably (e.g., Ayoub et al., 2019; Bengler et al., 2014; Kun, Boll, and Schmidt, 2016). Despite this technological progress, the path to fully self-driving vehicles without any human intervention is long, and for the foreseeable future human interaction is still needed with automated vehicles (e.g., Favarò, 2020; Janssen, Iqbal, Kun, and Donker, 2019; Kun 2016; Noy, Shinar, Horrey, 2018; Walch, Mühl, Kraus, Stoll, Baumann, Weber, 2017; Walch, Sieber, Hock, Baumann, and Weber, 2016).

Human-automated vehicle interaction can take at least two forms. One form is that of cooperation and collaboration, in which the human and the automated vehicle both contribute in parallel (shared control; e.g., Flemisch et al., 2012; Marcano et al., 2020; and see Inga et al., 2023 for a discussion on the even stronger form of 'symbiosis'). Within such cooperation and collaboration forms, responsibilities and subtasks of driving can be bebe dynamically divided explicitly or implicitly between the vehicle and the human (e.g., vehicle as a team player; e.g. Hoc et al., 2009; Walch et al., 2017). A second form is in transitions of control, where the automated system at times takes over full or partial control of the vehicle, but transitions control back to the human when desired by the human, or when required due to system limitations (e.g., Mirnig et al, 2017; Janssen, Iqbal, et al., 2019).

For both the cooperation/collaboration and the transition paradigm, it is important to have accurate models of human driving and interaction behavior. The goals of such models can be two-fold: (1) to inform the design of safe, efficient, and acceptable human-automated vehicle interaction strategies, and (2) to provide the automated system with a means to create an internal representation of the human. In the first case, such models could be used in simulation environments to predict the effects of human-automated vehicle interaction strategies on human behavior and experience. The availability of such models would reduce the amount of required empirical testing during the development of such interaction strategies and could accelerate this process significantly. In the second case, such models would be embedded into the algorithms of the automation, which would allow the automation to make estimations, for example, about the human's current understanding of the situation and the automation's current state and goals. This, in turn, would enable the automation to adapt its interaction strategies to the human's current state of situation understanding and to explain its own behavior efficiently and appropriately, which is a major prerequisite for successful human-machine cooperation (Hoc et al., 2009; Christoffersen & Woods, 2002). Based on information from the model, the automation would be better able to account for individual differences, such as those related to cognitive capacities, personality, or preferences.

A key tool in this regard is the use of *computational* cognitive models: computational instantiations that simulate the human thought process and behavior, and/or their interaction with an automated vehicle. Computational cognitive models build on a long tradition in cognitive science (e.g., Newell, 1990; Newell & Simon, 1972; Salvucci & Taatgen, 2011), human factors and human-computer interaction (e.g., Card et al., 1983; Oulasvirta et al., 2018; Kieras, 2012), neuroscience (e.g., Eliasmith, 2013; Marr, 1982), and AI and engineering (e.g., Goodfellow et al., 2016; Russell & Norvig, 2020). Today, there is a wide set of modeling methods and tools that can be applied to different domains, ranging from constrained theoretical problems to capturing real-world interaction (Oulasvirta, 2019).

Computational cognitive models have many benefits. They enforce a modus operandi of "understanding by building" and require precision in

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their specification (Newell, 1973; see also Brooks, 1993; McClelland, 2009; Pfeifer and Scheier, 2001). Models can test the impact of changes in parameters and assumptions, which allows for wider applicability and scalability (e.g., Anderson, 2007; Gray, 2007; Salvucci & Taatgen, 2011). More generally, this allows for testing "what if" scenarios. For human-automated vehicle interaction in particular, it allows testing of future adaptive systems that are not yet on the road.

Automated driving is a domain where computational cognitive models have large potential. Three modeling approaches have only started to scratch the surface. First, the large majority of current models focus on engineering aspects (e.g., computer vision, sensing the environment, flow of traffic) that do not consider the human extensively (e.g., Brackstone & McDonald, 1999; Helbing, 2001; Mogelmose, Trivedi, & Moeslund, 2012). Second, models that focus on the human mostly capture manual, non-automated driving (e.g., Salvucci & Taatgen, 2011; Brumby, Janssen, Kujala, & Salvucci, 2018; Jokinen, Kujala, and Oulasvirta, 2021). Third, models about human interaction in automated vehicles are either conceptual (e.g. Janssen, Boyle, Kun, Ju, & Chuang, 2019; Janssen, Iqbal, Kun, & Donker, 2019) or qualitative, and do not benefit from the full set of advantages that computational cognitive models offer.

In this introduction to a special issue and in the associated articles of the special issue, we assess where the field stands in more detail. We start with an overview of what we, as editors of the special issue, think the current stance of the field is, followed by an assessment of future directions and opportunities. We then close with an overview of the papers of the special issue.

2. Revisiting Newell's criteria: Where are we now?

One way to assess the current state-of-the-art is to compare it to the objectives that one of the pioneers of cognitive modeling, Allen Newell, laid out in his 1990 book on Unified Theories of Cognition (see pages 503-508). Although Newell wrote his outlook for the general field of computational cognitive modeling, we believe that these points (slightly rewritten by us below) also apply to the merger of computational cognitive modeling with the field of human-automated vehicle interaction:

(1) There should be multiple unified theories of cognition.
(2) Consortia are needed to make progress; individual researchers can not solve all phenomena.
(3) Be synthetic. That is: aim to integrate the ideas that come from competing theories to see where they are in common. If models are widely different, that might imply that there is not enough coherence.
(4) Be prepared to modify theories along the way, even radically, to make progress. Combined with point three: if some other theory has made progress in an area, all other theories could benefit from these insights.
(5) Have databases and benchmarks to test on.
(6) Make the models easy to use and easy to make inferences from.
(7) Find domains of practice.

So, where are we now in the area of human-automated vehicle interaction? This field in itself can be considered a domain of practice (point 7), however on the other aspects it seems that computational cognitive modeling of human-automated vehicle interaction is more in the starting blocks rather than a mature field.

Within the field, a variety of computational cognitive modeling techniques can be applied (point 1), as the articles in this special issue attest. Indeed, the wider field of human-computer interaction has a wide set of modeling techniques available (Oulasvirta, 2019; Murray-Smith et al., 2023; and see examples in this special issue for the application to human-automated vehicle interaction). However, these tend to come from relatively different modeling communities (for example processing models such as ACT-R, mathematical models such as DDMs, or machine learning models). Although there is cross-fertilization and inspiration, these models are not yet as synthetic in the sense that Newell proposed (point 3). Nonetheless, there is potential for synthesis; for example, by incorporating ideas on individual differences for which various articles in this special issue provide insights (e.g., Bachmann & Van Maanen, this issue; Fisher et al., this issue). This will require further modification (point 4).

Although databases exist with data from simulated and actual driving (point 5), the field of human-automated vehicle interaction at large mostly focuses on logging data from the car itself or from a fleet of vehicles (e.g., Barnard et al., 2016; Krajewski et al., 2018; Virginia Tech Transportation Institute, n.d.) Such data can give insights about scenarios where human intervention might be needed (e.g., situations where the car's performance fails and humans might give insight). However, such data might not be sufficiently rich to allow modeling of human behavior and thought in detail – as logging of human interaction might be missing, or not be at the fine-grained levels that some models need (for example, multiple milliseconds to second level for process models). Similarly, to the best of our knowledge, widely accepted benchmark tests for models of human behavior in automated vehicle contexts do not yet exist.

Consortia are needed (point 2), especially ones that can work multi- and interdisciplinary. To come to solutions that work in applications, insights are needed from multiple disciplines, for example, engineering (What are system requirements? How can algorithms be implemented?), social and behavioral sciences (What are limitations of the human mind, such as limitations to attention and memory?), humanities (What are the right ethical choices for implementing automated algorithms?), geosciences (How does the environment impact behavior?), law and economics (What types of algorithms are allowed in the car? To what degree can simulated humans take over control of a vehicle?), and design (How can interfaces be designed to support efficient human-automated vehicle interaction?). Multi- and inter-disciplinary collaboration was also part of the initiative for this special issue, namely a seminar at Schloss Dagstuhl on the topic (Janssen, Baumann, Oulasvirta, Iqbal, Heinrich, 2022) and it has also inspired other workgroups (e.g., Jeon et al., 2021).

Finally, once models are available, there is value in making them easy to use and easy to make inferences from (point 6). Specifically, computational cognitive models have the potential to be what Bonnie John called "cognitive crash dummies" (e.g., John, 2009). Although model-driven prototypes have been developed, such as Distract-R (Salvucci, 2009), to date these models have mostly been used for testing specific interactions within 1 vehicle, with preliminary work looking at the impact on other vehicles (e.g., Salvucci, 2013).

In other words: despite the high potential for the field (Newell's point 7) and the availability of many techniques (point 1), more progress still needs to be made on all other points.

3. Future directions and opportunities

3.1. Future research direction 1: Continuation of Newell's agenda, but applied to human-automated vehicle interaction

The first future research direction is to continue Newell's general research agenda for computational cognitive modeling for the specific area of human-automated vehicle interaction. How this applies to the field has been articulated above.

3.2. Future research direction 2: From isolated theory-slices to integrative theories

As described above the interaction of humans with automated vehicles in traffic is a highly relevant field of practice and application for cognitive computational models. Why is this so, from a more theoretical perspective? The driving task itself consists of many different subtasks that have to be carried out in a coordinated way, either by the human driver, by automation, or by human and automation together, to ensure safe, efficient, and comfortable transport both for the people sitting in the vehicle as well as for any other road users outside the vehicle (Hollnagel, Nabo, & Lau, 2003). Decisions about route selection have to be made, the environment must be monitored, and maneuvers have to be selected and executed in accordance with the current situation's requirements.

Consequently, the successful performance of the driving task by a human driver is the result of the integrated and coordinated operation of many basic psychological processes, such as perception, attention, memory, decision-making, and motor action. Understanding the interaction of humans with their (partially) automated vehicles has to take place in front of this background of human driving behavior and additionally has to include the processes that are added because of the introduction of the automation, such as monitoring the automation behavior and state, predicting its behavior, developing trust into it. Therefore, explaining and especially predicting humans' interaction behavior with automated vehicles requires describing the interaction of these many processes and how these interactions produce the observed human driving and interaction behavior in a given situation in a consistent and comprehensible way.

This in turn requires integrated models of human cognition as envisioned by Allen Newell (1990, see earlier discussion above) in his book on unified, integrated theories of cognition. Such models have the potential to capture a wide variety of highly relevant phenomena that cannot easily be evaluated with the very specific measures traditional cognitive science and engineering models usually apply (such as response times, or number of correct responses). Examples of such highly relevant phenomena that are the result of the complex interaction of basic cognitive processes are trust in automation, situational awareness, or the experience of comfort. Additionally, as the interactions underlying these phenomena are complex, models of such phenomena need to be described in a formal, computational way to ensure consistency and preciseness and to allow to derive testable and falsifiable predictions from these models.

Such models would represent a major step in understanding the complex phenomena of human behavior in a complex environment. They would help to overcome both the limitations of current engineering and cognitive science models of human (driving) behavior that mainly focus on very isolated aspects of human driving and interaction behavior and the limitations of the currently predominant box-and-arrow models of complex psychological phenomena, such as trust or situational awareness that are difficult to evaluate and even more difficult to be used as a source of predictions about human behavior. In other words, a future direction of the field is to move beyond "theory slicing" towards integrated models that capture more complex behavior. In this special issue, the paper of Held and colleagues and Fisher and colleagues represent examples of such highly needed integrated computation models of human-automated vehicle interaction.

3.3. Future research direction 3: Analysis versus embedding

Computational models of human-automated vehicle interaction offer not only the possibility for more consistent, precise, and comprehensive theory building of human cognition in a highly complex and dynamic application field. They can also be a tool both for the development and evaluation of interaction strategies and a means to provide an internal model of the human interaction partner for the automation. It is quite probable that different kinds of computational models are needed for different purposes. Models developed to explain human behavior and to identify causal relationships that underly human behavior require approaches that are transparent and allow the precise formulation of theories of the human mind. Cognitive architectures such as ACT-R (see Held et al., this issue; Fisher et al., this issue) are a prototypical example of an environment in which such models are developed.

Models that are applied as tools to evaluate the effects of human-automated vehicle interaction strategies basically need to provide valid, reliable, and reproducible input (the interaction strategies) - output (relevant aspects of human behavior) mappings that allow to predict the possible effects of different interaction strategies early on the development process. Such models offer the potential to reduce the amount of required empirical tests with real human participants and allow the simulation of much more interaction sequences than an empirical study would do.

Another class of goals for computational cognitive models of human-automated vehicle interaction consists of their embedding into the automation itself to provide the automation with an internal representation of the human interaction partner. One of the specific main requirements for these models is their need to be real-time capable. Of course, such models already exist for specific purposes, for example in the form of driver monitoring systems. These systems model different specific human states, such as drowsiness or distraction, based on the processing of observable parameters that are associated with the respective state. But focussing on very specific states these models underlying current systems are not able to exploit interactions between different states, such as the drowsiness-reducing effect of distracting tasks during a monotonous drive.

Currently, the development of computational models for different purposes takes place rather independently, driven by separated research teams in different research disciplines. Whereas computational models of human behavior for theory building are mainly applied by psychologists and cognitive scientists, computational models to be embedded into vehicle automation are mainly developed by engineers and computer scientists. Newell's point "be synthetic" is more than needed here to facilitate that the knowledge about the underlying cognitive processes of human driving and interaction behavior that is acquired with modeling approaches mainly intended to facilitate theory building will be used and is accessible for the computational models used as tools for interaction strategy evaluation and as models for the human user embedded into the vehicle automation. What is needed are ways to reliably transform the theory-driven computational models that are rigorously tested and evaluated in highly controlled experimental studies into real-time capable models that can be implemented into simulation environments and vehicle automation systems. Such reliable transformations would provide the less transparent, less theoretically motivated but highly performant computational models to profit from the testing of their source theory-based models, again improving and accelerating the development of vehicle automation that is adapted to human needs, capabilities, and limitations.

3.4. Future research direction 4: From description to prescription

Good theories are practical, as the popular mantra goes. But what does that mean in practice? We believe that many aspirations in modeling center on the possibility of counterfactual prediction: *What would happen if this event/action took place?* What would happen if transition would happen right now?; What would happen (in computational design) if the visualization of other cars was transparent and not opaque?; What would happen (interaction techniques) if the transfer function of this input device was like this and not like that?; What would happen if a notification was presented aurally and not visually?

We believe that cognitive modeling should not be 'just' about describing or explaining drivers behind human behavior, but it should equip the intelligent system to take safe and effective action with the human. Such models could be used for a variety of purposes:

1. Provide insights into usability and ergonomics before user testing
2. Helps test our understanding of driving and develop theory
3. Engineer better systems
4. Be embedded into real-world systems

These uses, however, bring up the challenge of counterfactuality that has not enjoyed the level of attention in research as it should. The AI needs to engage in 'what would happen if X happened?' type reasoning, and estimate the future consequences on the driver and the system as a whole. This problem has its corresponding problem in machine learning research: prediction for out-of-distribution samples. For example, changing conditions or counterfactual situations can cause 'distribution shift'. Suddenly predictions must be made for events that were not part of observation data so far.

What does this mean for computational models? It implies a hard challenge: we need to predict what will go on in the driver's mind, and how that will affect behavior, if a certain action is taken. This problem is incredibly hard for a number of reasons. First, inferring even the current latent state of the driver is hard and done under uncertainty. Second, any action can have a multitude of consequences. This means that errors in inference and prediction will compound more the longer the future one wants to predict.

3.5. Overview of papers in the special issue

This special issue had an open call for papers. Eventually, five papers made it through the peer-review process. The papers represent two broad modeling techniques: processing models within the ACT-R cognitive architecture (Held et al., this issue; Fisher et al., this issue) and drift-diffusion models or decision diffusion models (DDMs; Bachmann & Van Maanen, this issue; Theisen et al., this issue; Zgonnikov et al., this issue). In line with Newell's (1990) research agenda, the papers both reflect a diversity of "unified theories" in that different frameworks are represented, yet they also show synthesis in that single frameworks are used to test a wide set of questions and developments are inspired by an accumulation of evidence across fields. Moreover, similar research questions are addressed by different frameworks. For example, both ACT-R theories (Fisher et al, this issue) and DDMs (Bachmann & Van Maanen, this issue) study individual differences. Each paper represents methodological and theoretical innovations, for example, the attempt to make pure model-driven theoretical predictions about cognitive distraction (Held et al., this issue), and the ability to derive conclusions based on small sample sets (Bachmann & Van Maanen, this issue). Thematically, some papers mostly describe the interaction within the vehicle (Held et al, this issue; Bachmann & Van Maanen, this issue), the interaction between the vehicle and external traffic such as pedestrians (Theisen et al., this issue; Zgonnikov et al., this issue), or look at even wider scope of (remote) control of automation (Fisher et al., this issue). Overall, these papers represent an interesting set of models and model approaches that can inspire further research in the exciting field of computational cognitive modeling of human-automated vehicle interaction.

4. Conclusion

In conclusion, human-automated vehicle interaction is an exciting field to develop and evaluate computational cognitive models for. It can aid the field of human-automated vehicle interaction, but also provide novel insights on computational cognitive models itself due to the uniqueness of the field.

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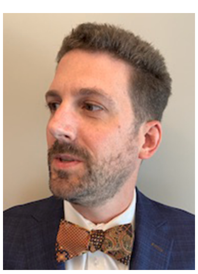

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