How Accurate Do the Models of Human Behavior Need to Be?

By Gustav Markkula and Mehmet Dogar

There are many examples of cases where access to improved models of human behavior and cognition has allowed the creation of robots that can better interact with humans, and not least in road vehicle automation, this is a rapidly growing area of research. Human–robot interaction (HRI) therefore provides an important applied setting for human behavior modeling—but given the vast complexity of human behavior, how complete and accurate do these models need to be? Here, we outline some possible ways of thinking about this problem, starting from the suggestion that modelers need to keep the

Models of Human Behavior for Human–Robot Interaction and Automated Driving

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right end goal in sight: a successful HRI, in terms of safety, performance, and human satisfaction. Efforts toward model completeness and accuracy should be focused on those aspects of human behavior to which interaction success is most sensitive.

We emphasize that identifying what those aspects are is a difficult scientific objective in its own right, distinct for each given HRI context. We propose and exemplify an approach to formulating a priori hypotheses on this matter in cases where robots are to be involved in interactions that currently take place between humans, such as in automated driving. Our perspective also highlights some possible risks of overreliance on machine-learned models of human behavior in HRI and how to mitigate against those risks.

INTRODUCTION

Human behavior does not cease to fascinate. While clearly rule bound and predictable in many ways, it is also consistently variable, adaptive, individual, or even (seemingly?) random. Unpeeling the layers of this complexity to better understand human behavior as well as the cognitive processes underlying it remains one of the most challenging and intriguing goals of science. For this reason, researchers across many disciplines (sociology, psychology, biology, and so on) develop models of how human behavior looks like and why, at a range of different levels of abstraction from conceptual to computational and from mechanistic to machine learned [1], [2].

Besides this push from fundamental scientific curiosity, there is also a pull in the form of various applied uses for such models, one of them clearly in HRI [3]. The HRI literature is full of examples where models of human behavior or cognition have been put to good use to improve the design of robotic agents interacting with humans [3]–[14]. From a behavior modeler’s perspective, this is great, fueling arguments in articles and funding proposals for the importance of modeling work. To do better HRI (or whatever application one focuses on), we must have better models of behavior. In practice, however, since human cognition and behavior are so endlessly complex, for this applied argument to work, modeling efforts ought to be focused where they are actually useful, which raises the important, yet rarely explicitly addressed, question: What exactly is it that needs modeling, and how accurate do the models need to be?

In this article, we will argue that this is a question of general relevance to HRI and that it is particularly pressing in the context of road vehicle automation. Next, we first provide some background on the use of human behavior models in HRI. We then discuss why models have been useful in these past settings, leading to the suggestion that modelers should explicitly consider the end goal of a successful HRI while scoping their modeling efforts. This leads on to a discussion on how to do this in practice, with concrete examples in vehicle automation and some thoughts on the role of mechanistic versus machine-learned models of human behavior as well as suitable next steps for research and development.

TYPICAL USES OF HUMAN MODELS IN HRI

We adopt an inclusive definition of a model of human behavior as any description of human behavior, regardless of whether that description is purely qualitative and conceptual or intricately quantitative and regardless of whether the description suggests underlying mechanisms or is purely phenomenological. As for conceptual models of human behavior, these have been put to use, especially in the high-level design of robots: for example, by first describing (i.e., modeling) the high-level strategies that humans adopt when handing over objects [4] or resolving conflicts in domestic locomotion [5] and then designing robots that tap into those same strategies.

More common in HRI, however, is the use of quantitative models capable of mathematically describing or predicting some aspect of how humans behave and/or cognitive mechanisms underlying that behavior. The most common way of leveraging such models in HRI is to integrate them into the robot’s algorithms for perception, planning, or movement. This, in turn, can serve a number of different (sometimes overlapping) purposes:

Some researchers have modeled humans to imitate human behavior at some level of abstraction. For example, by formulating a computational model of human–human object handover, one can then use this model directly in a robot controller [6], and models of human drivers’ speed- and lane-keeping can guide the motion control of automated vehicles (AVs) [7].

Another common approach is to use models that predict observable human behavior from the hidden states of the human to permit the robot to make inferences about human states from observation. With this type of approach, a robot can, for example, recognize human movement goals or intentions for short-term body movements [8] or longer-term locomotion [9]. The same general approach can also be applied to infer, for example, the attentional state [10] or social value orientation characteristics of human interaction partners [11]. Once the robot has access to estimates about the current states of the human, it can adapt its behavior to optimize the interaction accordingly.

A related type of optimization instead uses models to predict future human response to robot behavior to steer the interaction toward desirable human states or behaviors. For
example, robot behavior in forceful interactions, such as collaborative lifting, can be controlled to keep the human joint load or muscular effort within acceptable ranges [12]; models of how humans interpret robot behavior or utterances can help create more understandable robots for improved human performance in collaborative tasks [13], [14]; or likely human response to robot actions can be predicted to allow the robot to directly influence human behavior to achieve an intended interaction outcome [10].

Finally, quantitative human behavior models can also be used outside of robot algorithms altogether to test or benchmark robots in computer simulations. This is less common in general HRI but is of growing importance in vehicle automation for large-scale simulated testing [15] and for assessing AV performance in safety-critical situations against the benchmark of an attentive human driver performance model [16].

KEEPING THE END GOAL IN SIGHT

So why are human behavior models useful in the various examples reviewed previously? Simply put, it is because the models help achieve the end goal of a successful HRI (or they allow testing for that end goal). There are many possible metrics by which one might measure interaction success [17], [18], but we would suggest that all of them can be usefully subsumed under what are sometimes referred to as the three main goals of human factors engineering: safety, performance, and satisfaction [19].

It is worthwhile, however, to take a closer look at how, more precisely, the human behavior models help in these respects. We believe that the following roughly captures what is happening here. The reason human behavior can at all be modeled is that it has certain regularities (for example, due to stable underlying mechanisms). As illustrated in the—highly schematic—Figure 1, these regularities manifest themselves in the form of constraints on the behaviors expressed by humans during interaction with a robot, in terms of the following:

1) what behaviors are at all feasible, in the sense that they achieve the task at some minimum acceptable level of success and remain available to the human in the given state of the world (e.g., they do not require superhuman response times)

2) which of these behaviors the human would prefer to engage in.

Outside of the preferred envelope, human satisfaction and/or task performance drops, and outside of the feasible envelope, the interaction may fail completely, in some contexts with risks to human safety.

Under this conceptualization, the goal of human behavior modeling in HRI becomes one of promoting interaction success, by delineating the feasible or preferred behavioral envelopes of the humans with which the robot is interacting. In principle, the model could describe these envelopes explicitly, but the more common approach is instead that the model describes human behavior trajectories, and as long as these model trajectories stay inside of the true behavioral envelopes of the real human, this will still be helpful.

ADAPTING THE MODELING SCOPE TO AN HRI CONTEXT

THE MODELING SCOPE AS A CONTEXT-SPECIFIC RESEARCH QUESTION

In any given applied HRI setting, there are still myriad factors and mechanisms that might affect the trajectories and envelopes of human behavior. So still, the following question remains: What do we need to model and how accurately? Again, we think it is helpful to consider the end goal of interaction success, with the following implication: The more sensitive the interaction success in the given HRI context is to variations in a certain aspect of human behavior or cognition, the more accurate that part of the human model needs to be.

In relatively simple interactions, this is quite easy to see, especially in the hindsight of a successful implementation. For example, in the collaborative tea-making task in [13], quick human understanding of robot motion was key to an efficient interaction; hence, an accurate model of human motion understanding was helpful. However, since the humans were able to optimize their own object manipulations as they saw fit, a model of human limb movements would not have made any difference to the robot, whereas such a model was key to enabling smooth object handovers in the collaborative dish rack unloading task in [6].

FIGURE 1. A schematic illustration of preferred and feasible envelopes of task-achieving human behavior in interaction with a robot as well as possible impacts on the interaction if the robot behavior is such that the human cannot achieve the task within the preferred envelope, if at all.
Imperfections in these key parts of the human model will be particularly likely to cause the robot to force the human away from their preferred behavioral envelope, degrading the quality of the interaction. The actual consequences of such a degradation depend on the specific HRI context in various ways, some of which are listed in Figure 2. For example, if using a conceptual model of human locomotion conflict resolution to guide the design of a domestic robot [5], the result of an incorrect model may be experiment participants who achieve their tasks in a less satisfying or efficient way as well as the need to do another robot design iteration. In contrast, an inaccurate quantitative model of human behavior used in AV algorithms or testing regimes could result in pushing human road users all the way out of their feasible behavioral envelopes, with severe consequences.

Compared to the simple examples given with hindsight earlier, in a new or more complex HRI context, it may initially not be as clear what needs to be modeled. We suggest that in HRI contexts where the potential consequences of model imperfections are large, it is important to consider the question of what aspects of human cognition and behavior have the biggest impact on interaction success as a research question in its own right.

**ANSWERING THE RESEARCH QUESTION**

As with any research question, it may be possible to formulate sensible a priori hypotheses about the answer, perhaps especially so in cases where robots are to be involved in interactions that already take place between humans (such as object handover, collaborative assembly, interaction in road traffic, and so on). In such contexts, we would like to suggest that it may be useful to consider existing empirical research on human–human interactions (as well as introspection, to some degree) to attempt to answer the following question: How much could aspect X of human cognition/behavior be simplified in this human interaction before it yields significantly different interaction outcomes?

To clarify what we mean here, let us consider the two examples of road user interaction shown in Figure 3. Imagine that you are driving the blue car and that the surrounding gray vehicles are driven either 1) all by actual human drivers or 2) all by models of human drivers. For the simpler case of pure car following [Figure 3(left)], there exist many models of what perceptual quantities and motor strategies human drivers use to achieve this type of longitudinal control [20], but these details may not be of great importance for your interaction with the surrounding vehicles. As long as the gray vehicles keep their kinematics within typical ranges for human drivers (such as keeping speed up to make progress, avoiding excessive deceleration, and so on), you would possibly not perceive the interaction with these model-driven vehicles as significantly different from typical interactions with human-driven vehicles. These simple models could thus be regarded as human-like in a positive sense and could be perfectly useful for some HRI contexts, e.g., to generate human-like automated car following.

However, as also indicated in Figure 3, in the same simple car-following scenario, there may be a need to go beyond this positive human likeness and also consider the human tendency to sometimes not keep kinematics within typical human ranges. If, as you drive the blue vehicle, your gray lead vehicle never exhibits late reactions or excessive decelerations, then your interaction with it will be safer than with a human lead, so in this sense, the simplified model does yield a significantly different interaction outcome. This can be important if the intended use of the model in an AV is to predict the likely future behavior of human-driven lead vehicles, where overly benign model behavior could make for an AV that is not sufficiently defensive.

Again, however, it seems unlikely that very detailed models (e.g., of human visual time sharing or exact decision-making mechanisms) would be needed to achieve this fuller human likeness. Quite possibly, it could be enough to make sure that the ranges of kinematics covered by the model (for example, in the form of probability distributions) also include these more uncommon extremes [15].
If we now instead consider the other scenario shown in Figure 3, also including lane changes and merges, the list of behavioral phenomena to consider grows rapidly. Here, it seems unlikely that your interactions with models would have similar outcomes to those with humans if the model drivers did not have consistent goals over time; did not signal near-term intentions explicitly (i.e., turn indicators) and/or implicitly (e.g., lane positioning); or did not respond to such indications from you to also accommodate your goals to the extent expected given the local rules and norms.

While progress is being made in this area [11], [21], it remains an open question how to model these types of human road user behaviors, which may involve cognitive mechanisms such as theory of mind and social value orientation in decision making, and crucially, the listing of aspects of behavior in Figure 3 is still just an a priori hypothesis. To know which of these behaviors or mechanisms actually have the most impact on interaction success, dedicated empirical and modeling work will be needed.

A NOTE ON MACHINE-LEARNED MODELS
Note that we have not argued above that human behavior models need to be mechanistic. Data-driven, machine-learned modeling of human behavior is achieving increasingly impressive results and will likely be key to many application areas, not least vehicle automation [22]. According to what has been said here, as long as these models accurately capture those aspects of behavior that are important for interaction success, there should be no reason why they cannot achieve human likeness in the positive sense, without yet considering how to account for human shortcomings in these situations.

The previous examples illustrate what we mean by formulating hypotheses about which aspects of human behavior have an impact on interaction success in a given task context, based on reasoning from current human interactions. But in particular the latter example also illustrates how this research question may, especially for more complex HRI contexts, require iterative modeling and empirical work to reach an answer.

FIGURE 3. Example road user interaction scenarios as well as the human behaviors that a model would arguably need to replicate to achieve similar interaction outcomes to human drivers.

Keeping Kinematics Within Tolerable Ranges (Headway/Speed/Acceleration/Jerk)

Having Consistent Goals Over Time

Signalling Goals and Intentions to Others

Responding to Presence, Goals, and Intentions of Others

Following Rules and Norms for Priority

Positive Human Likeness

Full Human Likeness

Tendency to Sometimes Not Do These Things
aspects of human behavior that most affect interaction outcomes, all is good. However, it is important to note that the machine-learned models will not by themselves tell us what those key aspects of behavior are, so the research question emphasized in this article remains unanswered. In other words, until we have done the research to identify the aspects of human behavior to which a given interaction is most sensitive, we have no way of knowing whether the machine-learned models are fit for purpose. We think this insight highlights an important weakness in purely machine-learned modeling for HRI, but it also clearly indicates a path to addressing it.

**NEXT STEPS**

In our view, the most important next step in this area is to increase the focus on the key research question identified here: To what aspects of human behavior is HRI success most sensitive? This will require research leveraging both naturalistic and controlled empirical studies to understand what humans do (and how they do it) to achieve human–human interactions and HRIs that are successful (by some metrics, which may also need further development). These aspects of human behavior can then be targeted in modeling. The resulting improved human models can also be put to use to further address the same research question, for example, using ablation methods: Both in pure model simulation studies and in controlled studies where humans interact with model-controlled robots or with virtual humans, what model assumptions or capabilities make the biggest difference to interaction success?

**CONCLUSION**

We have argued that for applied HRI purposes, human behavior modelers should focus on those aspects of behavior to which the interaction outcome is the most sensitive, and the question of what those aspects of behavior are should be considered an important research question in its own right. Answering this question is not trivial and will require targeted research of its own, but the answers to it will tell us what needs modeling and what to look for when testing models (including machine-learned models). The exact requirements for model accuracy will vary between HRI contexts because the potential knock-on consequences of human model imperfection vary, with vehicle automation as a clear example of an application area warranting particularly high standards of accuracy for human behavior models.

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**REFERENCES**

[1] S. Farrell and S. Lewandowsky, *Computational Modeling of Cognition and Behavior*. Cambridge, U.K.: Cambridge Univ. Press, 2018.

[2] A. A. Moustafa, Ed. *Computational Models of Brain and Behavior*. Hoboken, NJ, USA: Wiley, 2017.

[3] A. Thomaz, G. Hoffman, and M. Cakmak, “Computational human-robot interaction,” *Found. Trends Rob.* vol. 4, nos. 2–3, pp. 104–223, 2016. [Online]. Available: http://www.nowpublishers.com/article/Details/ROB-049, doi: 10.15661/FTRSS.2015.X1.031.

[4] K. W. Strabala et al., “Towards seamless human-robot handovers,” *J. Human-Robot Interact.*, vol. 2, no. 1, pp. 112–132, 2013. [Online]. Available: http://dl.acm.org/citation.cfm?id=3019705.

[5] F. Babel et al., “Step aside! VR-based evaluation of adaptive robot conflict resolution strategies for domestic service robots,” *Int. J. Soc. Robot.*, vol. 15, pp. 1–22, Feb. 2022, doi: 10.1007/s12369-021-00858-7.

[6] C.-M. Huang, M. Cakmak, and B. Mutlu, “Adaptive coordination strategies for human-robot handovers,” in *Proc. Robot.*, Sci. Syst. XI, 2015, p. 31. [Online]. Available: http://www.roboticsproceedings.org/rss11/p31.pdf, doi: 10.15607/RSS.2015.XI.031.

[7] F. Hajisiejyvadi et al., “Effect of environmental factors and individual differences on subjective evaluation of human-like and conventional automated vehicle controllers,” *SSRN Electron. J.*, Preprint, Jan. 2022, doi: 10.31234/osf.io/65n79.

[8] J. Mainprice, R. Hayne, and D. Berenson, “Goal set inverse optimal control and iterative replanning for predicting human reaching motions in shared workspaces,” *IEEE Trans. Robot.*, vol. 32, no. 4, pp. 897–908, 2016, doi: 10.1109/TRO.2016.2581216.

[9] A. Rudenko, L. Palmieri, M. Herman, K. M. Kitani, D. M. Gavrila, and K. O. Arras, “Human motion trajectory prediction: A survey,” *Int. J. Robot. Res.*, vol. 39, no. 8, pp. 895–935, 2020, doi: 10.1080/02783649.2019.1697446.

[10] D. Sadigh, N. Landolfi, S. S. Sastry, S. A. Seshia, and A. D. Dragan, “Planning for cars that coordinate with people: Leveraging effects on human actions for planning and active information gathering over human internal state,” *Auton. Robots*, vol. 42, no. 7, pp. 1405–1426, 2018, doi: 10.1007/s10514-018-9746-1.

[11] W. Schwarting, A. Pierson, J. Alonso-Mora, S. Karaman, and D. Rus, “Social behavior for autonomous vehicles,” *Proc. Nat. Acad. Sci.*, vol. 116, no. 50, pp. 24,972–24,978, 2019, doi: 10.1073/pnas.1802671116.

[12] W. Kim, J. Lee, P. Peternel, N. Tsagarakis, and A. Ajoudani, “Anticipatory robot assistance for the prevention of human static joint overloading in human-robot collaboration,” *IEEE Robot. Automat. Lett.*, vol. 3, no. 1, pp. 68–75, 2018. [Online]. Available: http://ieeexplore.ieee.org/document/7987084/, doi: 10.1109/LRA.2017.2729666.

[13] A. D. Dragan, S. Bauman, J. Forlizzi, and S. Srinivasa, “Effects of robot motion on human-robot collaboration,” in *Proc. 10th Anna. ACM/IEEE Int. Conf. Human-Robot Interact.*, Portland, OR, USA, 2015, pp. 51–58, doi: 10.1145/2696454.2696473.

[14] S. Tellex, R. Knepper, A. Li, D. Rus, and N. Roy, “Asking for help using inverse semantics,” in *Proc. Robot.*, Sci. Syst. X, 2014, p. 24. [Online]. Available: http://www.roboticsproceedings.org/rss11/p31.pdf, doi: 10.15607/RSS.2014.X.024.

[15] S. Feng, X. Yan, H. Sun, Y. Feng, and H. X. Liu, “Intelligent driving intelligence test for autonomous vehicles with naturalistic and adversarial environment,” *Neurocomputing*, vol. 120, no. 4, p. 248, 2014, doi: 10.1016/j.neucom.2013.10.097.

[16] “Uniform provisions concerning the approval of vehicles with regards to automated lane keeping systems,” European Union, Brussels, Belgium, UN Regulation No. 157, 2021.

[17] A. Aly, S. Griffiths, and F. Stramandinoli, “Metrics and benchmarks in human-robot interaction: Recent advances in cognitive robotics,” *Cog. Syst. Res.*, vol. 43, pp. 313–323, Jun. 2017. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1389041716300912, doi: 10.1016/j.cosyst.2016.06.002.

[18] G. Hoffman, “Evaluating fluency in human–robot collaboration,” *IEEE Trans. Human-Mach. Syst.*, vol. 49, no. 3, pp. 209–218, 2019. [Online]. Available: https://ieeexplore.ieee.org/document/8678448/, doi: 10.1109/THMS.2019.2904558.

[19] J. D. Lee, C. D. Wickens, Y. Liu, and L. N. Boyle, “Introducing human factors into autonomous vehicles,” *Proc. 10th Annu. ACM/IEEE Int. Conf. Human-Robot Interact.*, Portland, OR, USA, 2015, pp. 51–58, doi: 10.1145/2696454.2696473.

[20] M. Safizzaman and Z. Zheng, “Incorporating human-factors in car-following models: A review of recent developments and research needs,” *Transp. Res. C, Emerg. Technol.*, vol. 48, pp. 379–403, Nov. 2014. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0968090X14002551, doi: 10.1016/j.trc.2014.09.008.

[21] K. Kang and H. A. Rakha, “A repeated game freeway lane changing model,” *Sensors*, vol. 20, no. 6, p. 1554, 2020, doi: 10.3390/s20061554.

[22] S. Suo, S. Regalado, S. Casas, and R. Urtasun, “TrafficSim: Learning to simulate realistic multi-agent behaviors,” in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2021, pp. 10,400–10,409, doi: 10.1109/CVPR46437.2021.01026.