Editorial
Special Issue on Computational Human Performance Modeling

HUMAN performance modeling (HPM) is a method of quantifying human behavior, cognition, and processes; a tool used by human factors researchers and practitioners for both the analysis of human function and for the development of systems designed for optimal user experience and interaction. Different from data-driven approaches (e.g., neural networks), most HPM approaches use "top-down" modeling methods based on the fundamental mechanisms of human cognition and behavior.

This special issue introduces several human performance modeling articles that make use of mathematical modeling, production systems, and formal methods. We hope that readers of the special issue can benefit from the variety of modeling articles using different modeling approaches. In the following paragraphs, we summarize the features of each modeling approach and briefly introduce the articles in this special issue.

I. Introduction to Mathematical Modeling

Mathematical equations can predict, quantify, and analyze human performance, workload, brain waves, and other indices of human behavior in a rigorous way. Compared with computer simulation, mathematical modeling has the following features:

1) Mathematical models and equations of human behavior quantify and extract the mechanisms of human behavior by through quantification of the relationships among variables, including the inputs and outputs of each equation.
2) These mathematical models can be easier for users to understand, and for extracting relationships among variables, than reading computer code.
3) Mathematical models and equations of human behavior are relatively easy to edit, modify, improve, and integrate with other models to develop entirely new equations.
4) Mathematical models and equations of human behavior and performance can easily be implemented with different programming languages and they can be imbedded in different intelligent systems to provide a basis for systems design.
5) Mathematical models and equations can lead to analytical solutions, which are more accurate than simulation (heuristic) results.
6) There are mathematical models and equations quantifying the entire human cognition system [1], [2], which is another unique feature of this particular approach.
7) There are mathematical models and equations that can be proved by derivation with no need for verification in terms of empirical data (e.g., [3]).

This last feature is one of the most important aspects of mathematical modeling. Mathematical modeling discovers relations among variables that may never been studied or explored by experimental studies and it sometimes opens "new doors" in scientific discovery. One typical example of mathematical modeling is the Theory of Relativity by Albert Einstein, which opened new doors in physics and has guided hundreds of experiments. However, mathematical models cannot completely replace production systems (computer code), as production systems can generate simulated behavior.

When a modeler constructs a new mathematical model of human performance, it is important for the modeler to clearly present each step in deriving the equations to minimize circular reasoning. In addition, modelers should clearly list all variable values (how they are set) and any free parameters in the model. The modeling articles in this issue follow these practices (see details in [4]).

The articles in this special issue that make use of mathematical modeling approaches, include: [item 1) in the Appendix] focuses on development of a novel mathematical model of human eye gaze behavior under workload, derived from the basic principle of information constrained control; and [item 2) in the Appendix] provides an example of mathematical modeling of human trust in dynamic human-machine interaction. The proposed model describes human trust levels as a function of experience, cumulative trust, and expectation bias. [Item 3) in the Appendix] describes a mathematical model to quantify drivers' attentional instability on a winding roadway.

II. Introduction to Production Systems

Production systems are a collection of "if-then" rules that represent human information processing of some cognitive task [5]. Newell and Simon [6] introduced production systems into cognitive psychology through their seminal book on human problem solving. A production system is characterized by an architecture that consists of two types of memories. A production memory holds the rules of the system and the content persists for the duration of system execution. Complementing production

Digital Object Identifier 10.1109/THMS.2019.2942742

memory is data memory, which stores dynamic information about the current task.

Early production systems served as models of specific cognitive skills. For example, Just and Carpenter [7] used a production system to characterize reading and comprehension. Also, Rouse *et al*. developed a production system to model operator fault diagnoses [8]. These models not only addressed cognitive skills, but also how tasks were procedurally performed [9].

As the field of cognitive psychology matured, "cognitive architectures" emerged to explicate principles of cognition. Production systems can be considered as a form of task-dependent cognitive architecture. Architectures such as Soar [10], the Adaptive Control of Thought [11], and the Model Human Processor (MHP) [12], [13] have provided not only a means to systematize productions but also a way of validating theories of cognition.

More recent developments include incorporating visual and auditory perception into cognitive architectures [14] and to more accurately represent temporal sequencing of executive processes [15]. Sequencing has been simulated using a Queueing Network-MHP (QN-MHP) architecture, which combines a queueing network with production rules.

In the current issue, Rhie *et al*. [item 4) in the Appendix] extend the QN-MHP framework to explore the relationship between sensory processes and deeper semantic properties. Specifically, they used oculomotor behaviors, such as reaction time and movement patterns, to explain cognitive levels of processing in a driving task.

III. Introduction to Formal Methods

Another active research area with a focus on human performance modeling relates to formal methods. Formal methods are mathematical techniques and tools that enable an analyst to specify, model, and formally verify the operation/behavior of systems [16]. The specification process rigorously describes desirable system properties (usually using different types of modal logic [17]) that engineers and analysts want to be true in a system. Modeling involves analysts using mathematical languages (usually based on state machines) to describe the behavior of the target system that they wish to analyze. The formal verification process then has the analyst mathematically prove whether the model satisfies the specification. This process can take a number of different forms including pen and paper proofs. However, modern approaches use software that enables semi-automated, and fully automated methods [18], [19].

Formal methods have been integrated into the engineering life cycle in a number of different capacities. This includes learning formal models of existing systems, analyzing models of legacy and new designs, generating implementations from formal models, and evaluating/validating implementations as being consistent with proved formal properties. Formal methods are extremely good at addressing unexpected problems caused by interactions between components in complex systems. As such, they have primarily been used in the design and analysis of computer hardware and software systems. Furthermore, a growing body of research has been investigating how they can be applied to human performance modeling to engineer safe and effective human–machine systems [20]–[22].

This special issue contains three articles, [items 5)—7) in the Appendix], that advance the use of formal methods with human performance modeling. In [item 5) in the Appendix], Abbate and Bass describe a novel method that accounts for "connectibility affordance" in formal verification analyses. This allows formal analyses to prove whether the capabilities of people in an environment and possible source-target connections (e.g., tubes connecting pieces of equipment) afforded by environmental objects will prevent unintended configurations. In [item 6) in the Appendix], Joo and Shin present a new formal framework that accounts for human-machine interaction in emerging adaptive automation in smart manufacturing systems. Finally, in [item 7) in the Appendix], Zhu *et al*. make use of a hidden Markov model (a probabilistic formalism) to discover two overriding strategies humans use to detect hacking of unmanned aerial vehicles. These three articles provide useful insights into where research in this area is headed. Traditional formal analyses that incorporate human performance modeling have focused on well-defined human task and cognitive models [20]. While useful, such approaches work best for addressing structured work. They do a poor job of accounting for unstructured work environments in which human behavior may be less predictable. The work on affordances presented by Abbate and Bass, [item 5) in the Appendix], provides knowledge of how formal methods can be used in unstructured environments to prove properties about system safety and resilience. Additionally, legacy formal human factors methods have tended to focus on system automation behavior, which is static and unchanging. However, with the proliferation of increasingly sophisticated automation that can behave autonomously and learn in response to environmental changes, formal methods (like those explored by Joo and Shin in [item 6) in the Appendix] will need to be developed to provide analysts with the capability to prove that human-automation interactions will be safe. Finally, traditional formal methods are discrete and do not account for stochastic behaviors. However, developments in probabilistic formal methods, like those in [item 7) in the Appendix], are beginning to be explored by human performance modelers and will enable analysts to account for uncertainty in human behavior and thus accurately assess the reliability of complex, human-interactive systems when absolute guarantees are not possible.

IV. Statistical Models

The remaining articles broadly fall under the category of statistical models. In [item 8) in the Appendix], Shi *et al*. developed an anomaly detection framework based on Bayes' theorem and metric learning. The authors were able to utilize multiple user feedback simultaneously. Their algorithm was tested in a user study. In [item 9) in the Appendix], Lu and Sarter discovered a relationship between automation reliability and eye movement data. They showed that people dwell more on low-reliable automation interfaces. In [item 10) in the Appendix], Shive *et al*. established statistical saliency as the relationship between the search time and the difference in a target item's features and the distribution of display features.

They then used the statistical saliency model to effectively color code maps by reducing search times.

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APPENDIX
RELATED WORK

1) R. M. Hecht, A. B. Hillel, A. Telpaz, O. Tsimhoni, and N. Tishby, "Information constrained control analysis of eye gaze distribution under workload," *IEEE Trans. Human-Mach. Syst.,* to be published, doi: 10.1109/THMS.2019.2930996.
2) W.-L. Hu, K. Akash, T. Reid, and N. Jain, "Computational modeling of the dynamics of human trust during human-machine interactions," *IEEE Trans. Human-Mach. Syst.,* to be published, doi: 10.1109/THMS.2018.2874188.
3) R. J. Jagacinski *et al.*, "Drivers' attentional instability on a winding roadway," *IEEE Trans. Human-Mach. Syst.,* to be published, doi: 10.1109/THMS.2019.2906612.
4) Y. L. Rhie, J. H. Lim, and M. H. Yun, "Queueing network based driver model for varying levels of information processing," *IEEE Trans. Human-Mach. Syst.,* to be published, doi: 10.1109/THMS.2018.2874183.
5) J. Abbate and E. J. Bass, "A formal approach to connectibility affordances," *IEEE Trans. Human-Mach. Syst.,* to be published, doi: 10.1109/THMS.2018.2886265.
6) T. Joo and D. Shin, "Formalizing human-machine interactions for adaptive automation in smart manufacturing," *IEEE Trans. Human-Mach. Syst.,* to be published, doi: 10.1109/THMS.2019.2903402.
7) H. Zhu, M. L. Cummings, M. Elfar, Z. Wang, and M. Pajic, "Operator strategy model development in UAV hacking detection," *IEEE Trans. Human-Mach. Syst.,* to be published, doi: 10.1109/THMS.2018.2888578.
8) Y. Shi, M. Xu, R. Zhao, H. Fu, T. Wu, and N. Cao, "Interactive context-aware anomaly detection guided by user feedback," *IEEE Trans. Human-Mach. Syst.,* to be published, doi: 10.1109/THMS.2019.2925195.
9) Y. Lu and N. Sarter, "Eye tracking: A process-oriented method for inferring trust in automation as a function of priming and system reliability," *IEEE Trans. Human-Mach. Syst.,* to be published, doi: 10.1109/THMS.2019.2930980.
10) J. Shive, S. Rosichan, S. Davis, C. Wade, J. Ellison, and S. Santoni-Sanchez, "The statistical saliency model can choose colors for items on maps," *IEEE Trans. Human-Mach. Syst.,* to be published, doi: 10.1109/THMS.2019.2901896.

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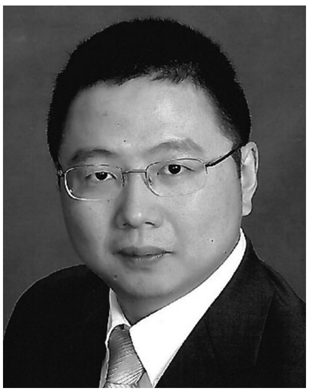

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