Ergonomics in Design: The Quarterly of Human Factors Applications

Human-Automation Interaction Research : Past, Present, and Future

Peter A. Hancock, Richard J. Jagacinski, Raja Parasuraman, Christopher D. Wickens, Glenn F. Wilson and David B. Kaber

The online version of this article can be found at:

Published by:

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On behalf of:

Human Factors and Ergonomics Society

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A range of perspectives on human-automation interaction may serve to sustain future performance in the area.

& Jex, 1967; McRuer, Allen, Weir, & Klein, 1977), between Bayesian decision models and models of the optimal estimation of noisy signals for vehicular control (e.g., Kleinman, Baron, & Levison, 1971), and between heuristic models of decision making and state space models of discrete control, such as the steering of large ships (e.g., Veldhuyzen & Stassen, 1977).

Analogous to signal detection theory (e.g., Swets, 1982), control theory has permitted researchers to separate strategic from underlying perceptual and/or stochastic limitations of human performance in target acquisition and continuous-tracking tasks in controlling complex automated systems (e.g., Jagacinski & Flach, 2003). However, unlike most common uses of signal detection theory, control theory does not typically categorize single actions or decisions in a sequence as correct or incorrect but, instead, describes the stability and efficiency of the extended sequence for reaching desirable goal states over time.

For example, how aircraft control dynamics influence the potential for oscillations or divergences from intended flight trajectories has been extensively studied. The redesign of aircraft that exhibit such tendencies may involve lowering control sensitivities, reducing lags, and/or filtering structurally resonant frequencies from the pilot's control movements (Committee on the Effects of Aircraft-Pilot Coupling on Flight Safety, 1997).

Related to the comments of Woods (Sheridan et al., 1998) on the historical function allocation problem, policy decisions in sociotechnological systems can be extremely difficult because of the complexity of system dynamics (e.g., Forrester, 1970). Such dynamics can also change with the introduction of new technology and lead to system instability.

Instances of people's collective inability to reach consensus on recognizing and/or controlling vehicular, financial, and ecological instabilities before they become harmful, such as the 2008 crash of the U.S. housing market, suggest that the quantitative predictions and qualitative intuitions based on control theory need to be more effectively utilized to debate options and to inform system designers on policy decisions involving humans and technology. The study of manual control (e.g., Jagacinski & Flach, 2003) can provide a relatively friendly introduction to relevant dynamic concepts for addressing such problems.

TRADE-OFFS IN HUMAN-AUTOMATION INTERACTION: ARE THEY INEVITABLE?
By Christopher D. Wickens

A long-held conventional wisdom is that a greater degree of automation in human-in-the-loop systems produces both costs and benefits to performance. Here *degree of automation* is defined both by higher levels of system autonomy (more machine authority on the Sheridan and Verplank, 1978, scale) and application to later stages of information processing (more automated action selection and execution

authority on the Parasuraman, Sheridan, & Wickens, 2000, taxonomy).

The major benefit of automation is performance in routine circumstances. Costs result when automation (or the systems or sensors controlled by automation) "fail" and the human must intervene, as in the crash of Air France Flight 447 (see Wise, 2011). This degraded failure response is assumed to result jointly from complacency (operator overreliance on automation) and from elimination of the so-called generation effect; that is, when operators are not involved in generating action alternatives. Together, these two effects define the loss of situation awareness (SA) at Level 1 (complacency) and Level 2 (the generation effect: one has reduced memory for actions one did not generate), based on Endsley's (1995) model.

Along with SA change, a second inferred variable is the reduction of workload that comes with greater degrees of automation, as humans are left with less to do. Thus the changes in these four variables (routine and failure performance, SA, and workload), produced by changes in degree of automation imply an elegant, but perhaps overly simplified, model. This conceptual model has historic threads that reach back through Billings's (1991) elegant work on human-centered automation, through early empirical and theoretical work on accidents induced by flight deck automation (Wiener & Curry, 1980) and the broader realm of other industrial environments (Rasmussen & Rouse, 1981).

However, the elegance of this intuitive linking of four variables brings with it the danger of oversimplification based on empirical findings that the trade-offs are far from inevitable. In 2010, Wickens, Li, Santamaria, Sebok, and Sarter (2010) reported that increased degree of automation to improve routine performance did not necessarily produce degraded failure response. What features, then, can mitigate the loss in failure performance with higher degrees of automation? Discovering these features provides the key to establishing useful guidelines for human-automation interaction. Some hints suggest that effective intuitive displays can buffer high levels of automation from human performance costs when things fail, perhaps capitalizing on principles of ecological interface design.

For example, Kaber, Perry, Segall, McClernon, and Prinzel (2006) demonstrated that auditory and visual cuing of adaptive automation with supervisory control of a telerover served to improve operator performance and reduce decrements in SA attributable to out-of-the-loop unfamiliarity. A second source of mitigation may be effective training: training to "expect the unexpected" as well as training in understanding of automation logic.

THE FOUNDATIONS OF ADAPTIVE AUTOMATION IN PHYSIOLOGICAL THEORIES
By Peter A. Hancock

The idea of having machines adapt to the cognitive and physical demands of users in a momentary and dynamic

manner (i.e., adaptive automation) is one of the more important ideas in the history of human factors/ergonomics. It has served to propel the field forward from its static incarnation of function allocations, such as was represented in the now famous Fitts list (Fitts, 1951), into something that has now exploited the extensive advantages of the computational revolution (Hancock & Scallen, 1996). However, the notion of dynamic adaptation itself was not really something new.

Indeed, the concept of adaptation was one that has permeated the annals of biology, even before its most famous formalization by Charles Darwin. But in biology, adaptation is accomplished almost exclusively by changes in the organism itself. Typically, these changes occur in proportion to the lifetime of the individual, and, thus, gradually, each species itself changes. But in the natural world, change happens on many time scales.

Can organisms change more directly in response to purposive elements in the environment? Although it is true that many animals use "tools" in the crudest sense of the word, the notion of orthotics being purposively produced by a species, which then itself subsequently co-adapts, is confined solely to human beings. Indeed, I would argue that this is one, if not the, central hallmark of humanity.

Formally, this co-adaptation occurs at a frequency that is derived from an integration of the respective time scales of change, as represented by variation rate in the organism and the tool, respectively. This characteristic interchange between humans and the machines they create, which I have elsewhere labeled the *self-symbiotic species,* is what makes human beings unique. Adaptive automation has served to take this, our form of hybrid development, one step further into the future.

Adaptation in human–machine systems was, from my perspective, first broached systematically at a behavioral level by Rouse, who sought to turn conflicting intelligences into cooperating ones (see Rouse, 1988). His work on the frustrations of dynamic incarnations of the Fitts list and MABA-MABA (men are better at–machines are better at)–like specifications began this important revolution, which is still controversial and playing out (see Dekker & Woods, 2002).

My own approach to the question of adaptive aiding derived from work in physiological systems and a number of associated efforts at modeling processing architectures and operational characteristics (Hancock, 1980). Indeed, the central question of adaptation is precisely how such sharing and dynamic task reapportionment could occur. The overall genre of thinking owes much to the pioneers of the cybernetic revolution. The challenge of how to specify what task elements were shared, when they were shared, and how they were shared was one that was not easily solved. I was fortunate to be able to work with my friend and colleague Mark Chignell on such issues. His computer-based insights meshed with my background in human biology as a basis for positing task load redistribution through analysis of observed physiological and neurophysiological signals. Our first published work on this approach to adaptive automation emerged

shortly afterward. For my own part, the publication was inspired by the seminal insights of scientists such as Bernard, Cannon, and Selye on stress-related regulation of central and peripheral nervous system operations (see Hancock, Chignell, & Loewenthal, 1985).

Others focusing on practical implementation have since advanced our original theoretical observations on such methods. These efforts led to and resulted in major research programs, including augmented cognition (Schmorrow, 2005) and neuroergonomics (Parasuraman & Rizzo, 2007), which are founded on these principles (see Parasuraman & Hancock, 2004).

Today, the partnership between humans and machines in complex systems is becoming ever more intimate. The significant advances in recording and interpreting physiological signals, especially those from the active central nervous system, have rendered what was once only a theoretical concept into a practical field technology. Not only can tasks be parsed according to which partner might be best able to deal with demands on a momentary basis, but one can also use technologies to provide to operators much wider access to computer-based information.

Examples of such adaptive automation technologies include the rotary pilots associate (RPA; see Miller and Hannen, 1999, for an assessment), which provided Apache pilots with the capability to negotiate with automation on flight task allocations and intelligently identified critical operation information to support performance. Thus, adaptation has now extended beyond the sharing phase to embrace a wider vista of augmentation, but in a true sense, this is adaptation at the "next level."

In the ongoing marriage of mind and machine, the neurophysiological portal through which a fuller integration could occur was opened marginally two decades ago by some promising theoretical conceptions. The present generation is passing rapidly through that conceptual window. However, this race for a greater human-machine intimacy may be more than simply another step along the unique road of history. For if the present vector of self-destructive progress continues, it may be that this avenue of development is the one that holds the greatest (some would say, only) promise for salvation.

TRACING THE HISTORY OF ADAPTIVE AUTOMATION
By Raja Parasuraman

Related to Hancock's account, the view that automation should be designed and implemented in an adaptive manner can be traced back to Licklider (1960), an early pioneer in computer science, following on the heels of Fitts's (1951) discussions of function allocation, as part of human factors science. In that era, automation was mainly applied to physical functions. As the trend toward greater computerization of the workplace continued, however, the possibility arose for automation of decision making and other cognitive functions.

Sheridan set the stage for the next development with his model of supervisory control, in which a human operator controlled a physical process through an intermediary computer (Sheridan & Verplank, 1978). A decade later, researchers such as Hancock et al. (1985), Parasuraman (1987), and Rouse (1988) suggested that such systems could benefit human performance if the nature of the interaction between the human and the computer was adapted to task or contextual demands.

Although these early conceptual and analytical efforts were important, what was missing was a body of empirical research that could test and validate the adaptive automation concept. Fortunately, funding for such research was initiated by the U.S. Navy, in the form of the Adaptive Function Allocation for Intelligent Cockpits (AFAIC) program in 1980, the basis for which was described in a technical report by Parasuraman, Bahri, Deaton, Morrison, and Barnes (1992). A key player in the development of that program was Michael Barnes, who has continued his interest in the adaptive automation concept to this day in his work on human interaction with unmanned vehicles (Barnes, Parasuraman, & Cosenzo, 2006). The AFAIC program led to a period of empirical research on the performance benefits and potential costs of adaptive automation (for reviews, see Inagaki, 2003; Scerbo, 2001).

Empirical research on adaptive automation has demonstrated its benefits with respect to mitigating, at least partly, some of the costs associated with human-automation interaction, such as unbalanced mental workload (Hilburn, Jorna, Byrne, & Parasuraman, 1997), complacency (Parasuraman, Mouloua, & Molloy, 1996), and reduced SA (Kaber, Wright, & Sheik-Nainar, 2006). At the same time, many issues concerning adaptive automation remain to be resolved, including the evaluation of different methods for adaptation, the relative merits of system- versus user-based adaptation, and refinement of neuroergonomic measures and algorithms.

Recent neuroergonomics research suggests that physiological measures—such as transcranial Doppler sonography for cerebral blood flow velocity (Shaw, Parasuraman, Guagliardo, & de Visser, 2010)—electroencephalography (Christensen, Estepp, Wilson, & Russell, 2012; Wilson & Russell, 2007), and heart rate (Ting et al., 2010), may be sensitive to unpredictable task load changes and useful for the application of adaptive automation in command and control tasks requiring information acquisition, analysis, and action implementation.

ONE THE USE OF PHYSIOLOGICAL MEASURES TO DETERMINE OPERATOR FUNCTIONAL STATE IN IMPLEMENTING ADAPTIVE AIDING
By Glenn F. Wilson

Adaptive aiding has been found to improve system performance by providing automation when an operator needs it. Because the aiding should be provided only when required to help a compromised operator, it is critical that the functional state of the operator be continuously monitored, otherwise the "aiding" may not be provided when needed or could be provided at the wrong time, interfering with the operator and resulting in increased demands on his or her cognitive resources.

As Parasuraman mentioned, there is a need for additional studies on methods of implementing adaptive automation. Determining when to provide adaptive aiding is especially difficult in highly automated systems in which the operator's role is primarily one of monitoring the system, as in advanced automated aircraft cockpits. In these situations, there is very little overt operator performance to observe in determining whether the operator could benefit from aiding. One method of determining when to provide aiding is to monitor the functional state of operators using data from their physiology.

Previous research has shown that these physiological signals can provide accurate estimates of operator functional state (OFS; Wilson & Russell, 2003a). This finding has been reported with regard to conditions such as mental workload. Brain, cardiac, and eye signals are particularly relevant features when deriving accurate estimates of OFS (Berka et al., 2004; Wilson & Russell, 2003b).

To accurately determine the functional state of the operator, several physiological measures are combined via a classifier. Various classifiers have been used to derive estimates of OFS, such as artificial neural networks, discriminant analysis, and support vector machines. The classifier is typically trained using data that represent the cognitive states of interest from each operator separately, or it is trained on previously obtained data from a group of similar operators. The trained classifier is then continuously provided with physiological data during task performance, which it uses to make estimates of the functional state of the operator. When the classifier determines that the operator requires assistance, the system is notified so that it can provide the appropriate automation.

As Miller and Hannen (1999) said of the RPA, the system provided pilots with the necessary information for effective flight control at critical times. This type of system requires embedding knowledge of the mission scenario (level of job demands) in the adaptation technology so that suitable aiding can be provided at any time during the mission.

Using these procedures, researchers have reported significant improvements in complex task performance (Wilson & Russell, 2007) for various applications, including unmanned (highly automated) aerial vehicle control. These results suggest that physiologically determined adaptive aiding may be included in future systems. Improvements in the areas of sensors, classifiers, and computing speed support this development.

SUMMARY AND CONCLUSIONS

Theories and principles of human-automation interaction and adaptive automation have come a long way since their origins in the 1950s and early '60s. From concerns about the real-world application of static function allocation (Fuld, 1993) emerged the promise of a solution through

adaptive allocation. Barriers to the practical realization of such structures came through definitions of types and levels of human-centered automation along with empirical research on conceptual forms of adaptive automation.

Demonstrations of model-based adaptive automation and benefits for human performance, workload, SA, and so on motivated work on more precise methods of adaptation to operator cognitive and physical needs. Physiologically based approaches to OFS assessment and connections with methods of task redistribution set the stage for near-real-time operator aiding under workload. Methods of neurophysiological imaging and neurophysiological techniques were a focus of the Augmented Cognition Program (Schmorrow, 2005), and research results provided a boost for adaptive automation applications. The emergence of neuroergonomics (Parasuraman & Rizzo, 2007) as a major area of research and practice in human factors/ergonomics has also continued this trend.

Now we are moving from progressively greater individual and task-related diagnosticity for adaptive function allocation toward a fuller agenda of human-machine intimacy. The benefit of our history is an understanding of previously unpredicted relationships of cognition and automation that appear to be mediated by human-machine system interface design and specialized approaches to training. Indeed, with certain physical orthotics and prosthetics now resident in the human individual, as well as emerging brain-computer interfaces (BCI; energized by the medical community), we are beginning to move from the birth of such conceptions into their viable childhood. For example, BCIs have been developed for adaptive robotic system control whereby the system responds to the "thoughts" of the human (Gergondet et al., 2011), which are mediated by workload states.

However, there remains a need to apply established theories (including control) to quantitatively predict optimal states of such human-machine symbiosis and provide a basis for ensuring complex dynamic system stability and performance in a range of operating conditions. Human factors engineers can provide designers with guidance on how to develop effective and intuitive forms of such interfaces for preventing automation costs, as Wickens suggests, and how to develop effective training programs for addressing unknown operating circumstances. What the fully mature hybrid human mind and automated machine integration will actually look like and how it will function is the reality the next generation will see and live in.

REFERENCES

Barnes, M., Parasuraman, R., & Cosenzo, K. (2006). Adaptive automation for military robotic systems. In *Uninhabited military vehicles: Human factors issues in augmenting the force* (NATO Pub. No. RTOTR-HFM-078, pp. 420–440). Brussels, Belgium: NATO.

Bartlett, F. C. (1962). The future of ergonomics. *Ergonomics*, *5*, 505–511.

Berka, C., Levendowski, D. J., Cvetinovic, M. M., Petrovic, M. M., Davis, G., Lumicao, M. N., . . . Olmstead, R. (2004). Real-time analysis of EEG indexes of alertness, cognition, and memory acquired with a wireless EEG headset. *International Journal of Human–Computer Interaction*, *17*, 151–170.

Billings, C. E. (1991). *Human-centered aircraft automation: A concept and guidelines* (NASA Technical Memorandum 103885). Moffet Field, CA: NASA Ames Research Center.

Christensen. J. C., Estepp, J. R, Wilson, G. F., & Russell, C. S. (2012). The effects of day-to-day variability of physiological data on operator functional state classification. *NeuroImage*, *59*, 57–63.

Committee on the Effects of Aircraft-Pilot Coupling on Flight Safety, National Research Council. (1997). *Aviation safety and pilot control*. Washington, DC: National Academy Press.

Dekker, S. A., & Woods, D. D. (2002). MABA-MABA or abracadabra? Progress on human–automation co-ordination. *Cognition, Technology and Work*, *1*, 240–244.

Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human Factors*, *37*, 32–64.

Fitts, P. M. (1951). (Ed.). *Human engineering for an effective air navigation and traffic control system*. Washington, DC: National Research Council.

Forrester, J. W. (1970). Systems analysis as a tool for urban planning. *IEEE Transactions on Systems Science and Cybernetics*, *SSC-6*, 258–265.

Fuld, R. B. (1993). The fiction of function allocation. *Ergonomics in Design*, *1*(1), 20–24.

Gergondet, P., Druon, S., Kheddar, A., Hintmuller, C., Guger, C., & Slater, M. (2011, December). *Using a brain-computer interface to steer a HRP-2 humanoid robot*. Paper presented at the IEEE International Conference on Robotics and Biomimetics (ROBIO), Phuket, Thailand.

Hancock, P. A. (1980). Simulated and experimental temperature responses in man during exercise in varying environments. *Computers in Biology and Medicine*, *10*, 1–9.

Hancock, P. A. (2008). Frederic Bartlett: Through the lens of prediction. *Ergonomics*, *51*, 30–34.

Hancock, P. A., Chignell, M. H., & Lowenthal, A. (1985). An adaptive human-machine system. In *Proceedings of 15th Annual IEEE Conference on Systems, Man and Cybernetics* (pp. 627–629). Washington, DC: IEEE.

Hancock, P. A., & Scallen, S. F. (1996). The future of function allocation. *Ergonomics in Design*, *4*(4), 24–29.

Hilburn, B., Jorna, P. G., Byrne, E. A., & Parasuraman, R. (1997). The effect of adaptive air traffic control (ATC) decision aiding on controller mental workload. In M. Mouloua & J. Koonce (Eds.), *Human-automation interaction: Research and practice* (pp. 84–91). Mahwah, NJ: Lawrence Erlbaum.

Inagaki, T. (2003). Adaptive automation: Sharing and trading of control. In E. Hollnagel (Ed.), *Handbook of cognitive task design* (pp. 147–169). Mahwah, NJ: Lawrence Erlbaum.

Jagacinski, R. J., & Flach, J. M. (2003). *Control theory for humans*. Mahwah, NJ: Lawrence Erlbaum.

Kaber, D. B., Perry, C. M., Segall, N., McClernon, C. K., & Prinzel, L. P. (2006). Situation awareness implications of adaptive automation for information processing in an air traffic control-related task. *International Journal of Industrial Ergonomics*, *36*, 447–462.

Kaber, D. B., Wright, M. C., & Sheik-Nainar, M. (2006). Multimodal interface design for adaptive automation of a human-robot system. *International Journal of Human-Computer Studies*, *64*, 527–540.

Kleinman, D. L., Baron, S., & Levison, W. H. (1971). A control theoretic approach to manned-vehicle systems analysis. *IEEE Transactions on Automatic Control*, *AC-16*, 824–832.

Licklider, J. C. R. (1960). Man-computer symbiosis. *IRE Transactions on Human Factors in Electronics*, *HFE-1*, 4–11.

McRuer, D. T., Allen, R. W., Weir, D. H., & Klein, R. H. (1977). New results in driver steering control models. *Human Factors*, *19*, 381–397.

McRuer, D. T., & Jex, H. R. (1967). A review of quasi-linear pilot models. *IEEE Transactions on Human Factors in Electronics*, *HFE-8*, 231–249.

Miller, C. A., & Hannen, M. D. (1999). The rotorcraft pilot's associate: Design and evaluation of an intelligent user interface for cockpit information management. *Knowledge-Based Systems*, *12*, 443–456.

Parasuraman, R. (1987). Human-computer monitoring. *Human Factors*, *29*, 695–706.

Parasuraman, R., Bahri, T., Deaton, J. E., Morrison, J. G., & Barnes, M. (1992). *Theory and design of adaptive automation in aviation systems* (Tech. Rep. No. NAWCADWAR-92033-60). Warminster, PA: Naval Air Warfare Center, Aircraft Division.

Parasuraman, R., & Hancock, P. A. (2004). Neuroergonomics: Harnessing the power of brain science for human factors and ergonomics. *Human Factors and Ergonomics Society Bulletin*, *47*(12), 1, 4–5

Parasuraman, R., Mouloua, M., & Molloy, R. (1996). Effects of adaptive task allocation on monitoring of automated systems. *Human Factors*, *38*, 665–679.

Parasuraman, R., & Rizzo, M. (Eds.). (2007). *Neuroergonomics: The brain at work*. New York, NY: Oxford University Press.

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model of types and levels of human interaction with automation. *IEEE Transactions on Systems, Man and Cybernetics*, *30*, 286–297.

Rasmussen, J., & Rouse, W. B. (Eds.). (1981). *Human detection and diagnosis of system failures*. New York, NY: Plenum Press.

Rouse, W. B. (1988). Adaptive aiding for human/computer control. *Human Factors*, *30*, 431–438.

Scerbo, M. (2001). Adaptive automation. In W. Karwowski (Ed.), *International encyclopedia of human factors and ergonomics* (pp. 1077–1079). London, UK: Taylor and Francis.

Schmorrow, D. D. (Ed.). (2005). *Foundations of augmented cognition*. Mahwah, NJ: Lawrence Erlbaum.

Shaw, T., Parasuraman, R., Guagliardo, L., & de Visser, E. (2010). Towards adaptive automation: A neuroergonomic approach to measuring workload during a command and control task. In *Proceedings of the 3rd International Applied Human Factors & Ergonomics Conference* (CD-ROM).

Sheridan, T., Hancock, P. A., Pew, R., Van Cott, H., & Woods, D. (1998). Can the allocation of function between humans and machines ever be done on a rational basis? *Ergonomics in Design*, *6*(3), 20–25.

Sheridan, T. B., & Verplank, W. L. (1978). *Human and computer control of undersea teleoperators*. Cambridge, MA: MIT Man–Machine Systems Laboratory.

Swets, J. A. (1982). Sensitivities and specificities of diagnostic tests. *Journal of the American Medical Association*, *248*, 548–549.

Ting, C., Mahfouf, M., Nassef, A., Linkens, D. A., Panoutsos, G., Nickel, P., Roberts, A. C., & Hockey, G. (2010). Real-time adaptive automation system based on identification of operator functional state in simulated process control operations. *IEEE Transactions on Systems, Man and Cybernetics. Part A: Systems and Humans*, *40*, 251–262.

Veldhuysen, W., & Stassen, H. G. (1977). The internal model concept: An application to modeling human control of large ships. *Human Factors*, *19*, 367–380.

Wickens, C., Li, H., Santamaria, A., Sebok, A., & Sarter, N. (2010). Stages and levels of automation: An integrated meta-analysis. In *Proceedings of the Human Factors and Ergonomics Society 54th Annual Meeting* (pp. 389–393). Santa Monica, CA: Human Factors and Ergonomics Society.

Wiener, E., & Curry, R. (1980). Flight deck automation: Promises and problems. *Ergonomics*, *23*, 995–1012.

Wilson, G. F., & Russell, C. A. (2003a). Operator functional state classification using psychophysiological features in an air traffic control task. *Human Factors*, *45*, 381–389.

Wilson, G. F., & Russell, C. A. (2003b). Real-time assessment of mental workload using psychophysiological measures and artificial neural networks. *Human Factors*, *45*, 635–643.

Wilson, G. F., & Russell, C. A. (2007). Performance enhancement in a UAV task using psychophysiological determined adaptive aiding. *Human Factors*, *49*, 1005–1019.

Wise, J. (2011). What really happened aboard Air France 447? *Popular Mechanics*. Retrieved from http://www.popularmechanics.com/technology/aviation/crashes/what-really-happened-aboard-air-france-447-6611877

Peter A. Hancock is Provost Distinguished Research Professor and Pegasus Professor in the Department of Psychology and the Institute for Simulation and Training at the University of Central Florida. He is a Fellow and past president of the Human Factors and Ergonomics Society. His current work concerns human relationships with technology and the mystery of time.

Richard J. Jagacinski is a professor of psychology at The Ohio State University with a joint appointment in integrated systems engineering. In his teaching and research, he explores quantitative models of perceptual-motor coordination, the relation between control and decision problems, and behavioral effects of aging.

Raja Parasuraman is university professor of psychology at George Mason University. He has long-standing research programs in human factors and cognitive neuroscience. He has been concerned with the role of human attention, memory, and vigilance in automated and robotic systems while also investigating cognitive neuroscience of attention. He has merged interests in human factors/ergonomics and cognitive neuroscience by founding and developing the field of neuroergonomics, which he defines as the study of brain and behavior at work.

Christopher D. Wickens is a professor emeritus and former head of the Human Factors Division of the Beckman Institute at the University of Illinois at Urbana-Champaign. He is a senior scientist with Alion Sciences and an adjunct professor at the University of Colorado. His research focuses on the psychological dimensions of human attention related to the performance of complex tasks and a human factors/ergonomics perspective on how displays and automation can be used to support operator behavior in high-risk systems.

Glenn F. Wilson is president and principal scientist of Physiometrex, Inc. He recently retired from Wright-Patterson Air Force Base, where he worked as a research psychologist. His research interests are centered on using psychophysiological measures to monitor operator functional state. He has used laboratory, simulator, and flight environments in many studies of such measures.

David B. Kaber is a professor of industrial and systems engineering at North Carolina State University and associate faculty in biomedical engineering and psychology. He is a recent Fellow of the Human Factors and Ergonomics Society. His research interests include computational modeling of human cognitive behavior in interactions with advanced automated systems and optimizing the design of automation interfaces based on trade-offs in information load, task performance, and cognitive workload.