Integrating Humans With and Within Complex Systems

Challenges and Opportunities

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Abstract. The integration of humans with and within today's ever more complex and increasingly more adaptive software and systems poses an ever-growing challenge. This paper discusses this integration challenge from the perspective of capitalizing on the strengths of humans, software, and systems while circumventing their respective limitations. Specific findings and examples of integration challenges that go beyond the usual human factors perspective are presented. The paper concludes with a research agenda for advancing the state-of-the-art in integrating humans with adaptive software and systems.

Introduction

The potential for "disconnect" between people and technology is well-documented in the literature for both consumer products and large scale defense, energy, and transportation systems [1, 2, 3]. The Patriot missiles deployed in the 2003 Iraq war offer an excellent illustration of this disconnect. Operators of this missile were trained to trust the system's software because the Patriot missile is a highly automated system. Such trust is essential especially when operating in a heavy missile attack environment [4]. This was not the case in the Iraqi battlespace in which the missile batteries were operating in an environment sparsely populated with missiles but with several friendly aircraft. The inadequately trained missile operators were unaware that the Patriot radar system was susceptible to recording spurious hits and occasionally issuing false alarms (i.e., mistaking friendly aircraft for enemy missiles) without displaying the uncertainty in target identification. Not surprisingly, these operators tended to trust the system's assessments and missile launch decisions against potentially hostile targets. These factors were in play in the unfortunate shoot down of a British Tornado and a U.S. Navy F/A-18. A Defense Sciences Board study concluded that, "more operator involvement and control in the function of a Patriot battery" was necessary to overcome the system's limitations [4]. Despite this recognition, system operators continue to be unfairly blamed for systemic failures. This fact did not go unnoticed by Chiles [2] who cautioned, "Too often operators and crews take the blame after a major failure, when in fact the most serious errors took place long before and were the fault of designers or managers whose system would need superhuman performance from mere mortals when things went wrong."

The primary design flaws that Chiles refers to were largely failures in proper coordination of interactions between people and technology during system development and operation [5]. In recent years, the need for systems to become increasingly more adaptive to cope with changes in the operational environment has made the integration of humans with software and systems even more challenging. In response to these challenges, the DoD made a concerted push to incorporate human considerations into the systems engineering lifecycle [6]. This emphasis led to the creation of the new multidisciplinary field of Human Systems Integration (HSI) [7, 8]. HSI is the study of interactions between humans and systems to produce human-system designs that are compatible, safe, consistent, and efficient. These interactions continue to become increasingly more complicated as human roles continue to evolve from that of an operator outside the system to that of an agent within the system. Compounding the problem is the fact that misconceptions about what it takes to integrate humans with software and systems continue to linger in the software and systems engineering communities [9]. Perhaps the single biggest misconception is that humans are "suboptimal job performers." This mindset leads to software and systems that are specifically designed to shore up or compensate for human shortcomings. With this mindset, it is hardly surprising that humans are forced to operate or work within systems that are inherently incompatible with their conceptualization of work. This paper reviews what we know about humans, discusses the consequences of unwarranted assumptions in design, and presents a HSI research agenda to advance the state-of-the-art in developing adaptive human-machine systems.

What We Know About Humans

Humans have specific strengths and limitations that need to be well-understood before determining how best to integrate them with software and systems [10, 11, 12, 13]. The key findings from the literature that bear on human-system integration are:

- **Human Performance:** [14, 15, 16, 17]
  -Varies nonlinearly with several factors
  -Follows an inverted U-curve relative to stress
  -Excessive cognitive complexity can lead to task shedding and poor performance [14]
- **Human Error:** [14, 16]
  -Lack of inspectability into system operation can induce human error
  -Incompatibility between human processes and machine algorithms can lead to human error
  -Sustained cognitive overload can lead to fatigue and human error
- **Human Adaptivity:** [18, 19]
  -Adaptivity is a unique human capability that is neither absolute or perfect
  -Humans do adapt under certain conditions but usually not quickly
  -Human adaptation rate sets an upper bound on how fast systems can adapt
  -Tradeoff between human adaptation rate and error likelihood
  -Need to define what is acceptable error rate (context-dependent)

- **Multitasking:** [18, 19]
  -Humans do not multitask well
  -Stanford University's research findings show that so-called high multitaskers have difficulty filtering out irrelevant information, can't compartmentalize to improve recall, and can't separate contexts
- **Decision Making Under Stress:** [18, 19]
  -Under stress humans tend to simplify environment by disregarding/underweighting complicating factors
  -Reduced ability to process multiple cues or perform tradeoffs
- **User Acceptance:** [14, 18, 19]
  -Overly complex system design can lead to rejection of the system
  -Humans do not have to really understand software/system operation to develop confidence and trust in system
- **Risk Perception and Behavior:** [20, 21, 22, 23, 24]
  -Humans accept greater risks when in teams
  -Humans have a built in target level of acceptable risk
- **Human-System Integration:** [9, 25, 26]
  -Humans are creative but rarely exactly right; however, human errors usually tend to be relatively minor
  -Software/system solutions tend to be precisely right, but when wrong they can be way off

The literature on human-machine systems offers ample evidence that poorly designed automation can produce performance degradation of the overall human-machine system. An important aspect of such performance degradation is the lack of "fit" between the mental models of humans, cognitive demand of the work environment, and automation design.

Poor Automation Design Can Degrade Human Performance

- **Cognitive Load in Supervising Automation:** [27, 28]
  -The cognitive load when monitoring automated task performance can outweigh potential automation benefits
- **Automation-induced Complacency:** [29]
  -Over-reliance on automation can increase errors as humans begin to rely on automated cues rather their own vigilant information seeking and cognitive processing [30]
- **Partially Automated System with Incomplete Knowledge:** [31]
  -The system, operating outside its competence regime, stays in the loop and continues to critique operator performance based on erroneous assessment of work constraint violations
- **Mistrust of Automation:** [1]
  -Can lead to disuse, neglect, underutilization
  -Typically arises from poor design (e.g., high rate of false alarms in an alerting system)
- **Erosion of Operator's Expertise and Engagement:** [32]
  -Inappropriate automation can lead to skill decay or dysfunctional skills
  -Operator can no longer intervene effectively when automation malfunctions

Unwarranted Assumptions in Design Can Produce Unintended Consequences

System designs are often based on unstated and occasionally unwarranted assumptions about human behavior. These assumptions can often lead to unintended consequences and give rise to systemic failures. The following paragraphs offer examples of unexpected outcomes and unintended consequences that can be traced to unwarranted assumptions about human behavior:

Risk Homeostasis: Wilde specifically hypothesized that humans have a target level of acceptable risk (that typically varies among humans but is fixed for each individual). He called this risk homeostasis. He argued that safety features and campaigns tend to shift rather than reduce risk. While initially subject to criticism, this hypothesis was confirmed through studies in Munich, Germany, and in British Columbia, Canada. In the Munich study, half a fleet of taxicabs was equipped with anti-lock brakes (ABS), while the other half was provided conventional brake systems. Pursuant to testing, it was discovered that the crash rate was about the same for both types. Wilde concluded that this result was due to the fact that drivers of ABS-equipped cabs took more risks because they assumed that the ABS would provide the requisite protection in hazardous driving conditions. By the same token, the non-ABS drivers drove more carefully because they recognized that they were driving without an ABS system and had to be more careful in hazardous driving conditions.

Design-induced Human Error: In 2008, a Metrolink commuter train crashed headlong into a Union Pacific freight locomotive after going through four warning lights. The engineer (i.e., the driver) failed to hit the brakes before the train crashed. A teenage train enthusiast later claimed to have received a cell phone text message from the driver a minute before the collision [3].

So, was the Metrolink train accident a human error, a systemic problem that manifested itself as a human error, or both? The answer is BOTH. Since the driver was doing a split-shift, he was clearly tired. He was also multitasking. Humans don't multitask well and are error-prone in such circumstances. However, the system was also not designed for integration with the human in that the system design assumed an optimal human i.e., one who could multitask, one who would not fatigue, and one who was goal-driven and a utility maximizer. Humans are not any of these! This was an accident waiting to happen [9].

Human Role-Architecture Mismatch: The human role in relation to the system or within the system plays a significant role in both system architecture design and algorithm selection. For example, if the human is expected to be replaced by automation in the future, then the system architecture would emphasize a different set of quality attributes than if the human role was integral to the system (i.e., permanent). The same is true of algorithm selection. Consider the selection of a route planning algorithm for an autonomous ground vehicle. Invariably, a constrained optimization algorithm would be used to solve the route planning problem. Now consider route planning for a human-supervised ground vehicle in which the human needs to specify waypoints along the way. In this case, the algorithm needs to be interactive, inspectable, and understandable so that the human can intervene to specify waypoints. As such, a heuristic algorithm becomes preferable to the optimization algorithm because the heuristic algorithm allows the human to understand system reasoning and intervene effectively [33]. In this example, algorithm inspectability is more important than algorithm optimality.

Indiscriminate Automation: Roughly a decade ago, a blind side indicator was developed for automobiles to show an object in the driver's blind side. This device was never approved, because behavioral research showed that drivers were going to overuse the indicator, and no longer bother to look back over their shoulder when changing lanes. This would have been clearly an undesirable change in driver behavior. The lesson clearly is that indiscriminate use of technology without understanding its impact on human behavior patterns can potentially change human behavior, and not necessarily for the better. This kind of analysis is key to avoiding unintended consequences [33, 34].

The foregoing examples provide several key insights. First, in a tightly coupled system, any change to the machine will cause humans to change as well. Such a change could be undesirable in the sense that it could lead to unintended consequences. Second, unwarranted assumptions about the human can lead to tragic accidents [33]. For example, assuming that humans are optimal information processors can lead to dire results because humans do fatigue and don't multitask well. Third, the role of the human in the overall system is key to architectural paradigm and algorithm selection. Specifically, it is important to determine whether the human is central to system operation, or merely an adjunct or enabler to be replaced by automation in the future. Fourth, system architects need to focus on combined human-system performance, not the performance of each in isolation. This also means that the focus should be on combined metrics, not individual metrics. And, finally, a change in the operational environment can potentially change how people perceive and compensate for risks [9].

HSI Research Agenda

Figure 1 presents a HSI research framework for investigating high payoff research opportunities. As shown in this framework, HSI research needs to address human capabilities and limitations, evolving human roles, system adaptation contexts, and the systems engineering lifecycle.

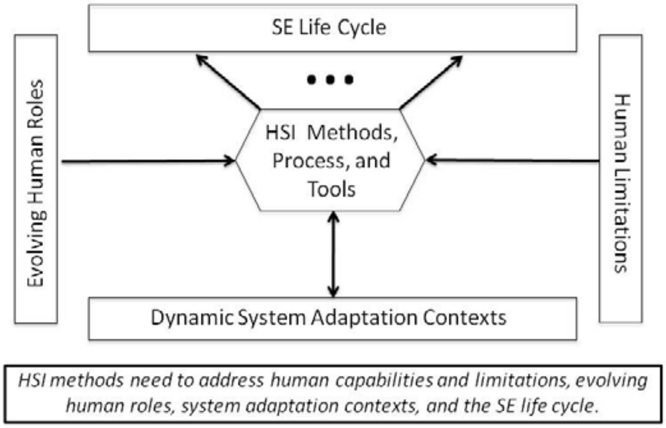

Figure 1: High Payoff HSI Research

This framework, in part, is inspired by the recently completed DoD-sponsored National Research Council (NRC) study [8], which recommended: (a) the development of shared representations to enable meaningful communications among hardware, software and HSI designers as well as within the human-system design group, and within the stakeholder community; (b) the extension and expansion of existing HSI methods and tools including modeling and simulation methods, risk analysis, and usability evaluation tools; and (c) the full integration of humans with engineered systems. In light of these recommendations, several research thrusts need to be pursued before developing HSI methods, processes, and tools for infusing HSI considerations into the software and systems engineering lifecycle. These research thrusts are discussed next:

Methodology for HSI Problem Identification: The underlying HSI problems could be one or more of the following: system is too difficult to operate, human error rates are unacceptably high, system is not being used or is not being used as intended, system is too hard to maintain, system is too expensive, and system does not scale. To this end, research is needed in advancing the state-of-the-art in concept engineering, virtual prototyping, interactive human-system simulations, human behavior and performance modeling, behavioral informatics, and synthetic environments that capture the geospatial and socio-cultural characteristics of the operational environment.

Development of a Shared Representation: In keeping with the NRC's recommendation, the development of a shared representation is key to enabling meaningful communication and collaboration among hardware engineers, software engineers, HSI personnel, and the larger stakeholder community. To this end, the development of a common ontology and a lexical data base that eliminates the polysemy and synonymy problems among the different disciplines can serve as a sound starting point.

Expansion of Existing Methods and Tools: Existing modeling and simulation tools as well as risk analysis and usability evaluation methods have focused on front-end analysis with a narrow view of human-system integration [8]. Research is needed to extend the methods, processes, and tools to span the full software and system lifecycles while also expanding the scope of the modeling, simulation and analysis tools to address human integration with adaptive systems.

Human Performance Modeling: Human performance varies nonlinearly with a variety of factors such as stress, anxiety, workload, fatigue, and motivation levels. For example, the Yerkes-Dodson law shows that as stress increases, so does performance, up to a point beyond which it rounds out and starts decreasing (the well-known inverted U-Curve). Cognitive workload becomes a key concern in several mentally taxing functions/jobs [10, 11, 35] such as anesthesiology, air traffic control, military command and control, and nuclear power plant operation. The key characteristics of high cognitive load tasks are that they are stimulus-driven (i.e., not self-paced), they produce large fluctuations in demand, they involve multi-tasking, they generate high stress and, they tend to be highly consequential [9]. Research is needed in developing adaptive human performance models and simulations that are sensitive to the various factors that affect performance. Such models can then be used to "test drive" and evaluate candidate designs from an HSI perspective.

Architecture Design: The architectural design of adaptive human-machine systems is highly dependent on the roles that humans play and the transition between roles in the overall adaptive system. In particular, human roles have a significant impact on the architecture depending on whether the human is central to the system, a monitor of the system with override privileges, or merely an enabling agent [9]. Research is needed in adaptive architecture design with various levels of human involvement in system operation. In particular, a human performance testbed needs to be developed that can support architecture sensitivity analysis to changes in critical human and environmental parameters and architecture adaptation in response to changes in these parameters.

Consolidating Human Performance Body of Knowledge: At the present time, the body of knowledge in human performance is highly fragmented. Exemplar categories include: human adaptivity contexts and rates; workload (cognitive and psychomotor); decision making (under time-stress, uncertainty, and risk); risk perception and risk homeostasis; socio-cultural factors in decision making, negotiations, and consensus building; vigilance and arousal; and physiological/mental stress, and fatigue. Research is needed to determine where and how these various considerations interact and then to consolidate the body of knowledge with use cases that reflect the needs of systems engineers, software engineers, and HSI practitioners.

Integrated Aiding-Training Continuum: Recent research has shown that aiding and training lie along a human performance enhancement continuum [12]. Research is needed in defining adaptive architectures for integrated aiding and training, capable of dynamically repurposing content (e.g., Shareable Content Objects) for aiding, training, and performance support based on user needs and the operational context [35].

HSI Patterns: Humans interact with systems differently based on their role (i.e., supervisor, monitor, enabler) relative to the system. Human-system interaction for each role and transition between roles tends to be different and potentially amenable to characterization through patterns. For example, the transition of human role from a supervisor to an enabler based on changes in context can be characterized by a pattern. Research is needed in defining the adaptation requirements of various types of architectures based on role transitions and capturing these findings in the form of HSI architectural patterns.

Conclusions

The systems acquisition and engineering communities have recently began to focus on addressing human capabilities and limitations and their implications on the design, operation and maintenance of complex systems. The discipline of HSI is intended to remedy this problem. However, for HSI to make inroads into the systems acquisition and engineering communities, several advances need to occur. First, the fragmented body of knowledge in human performance needs to be consolidated, expanded, and transformed into a form that lends itself to being incorporated into software and systems engineering practices. Second, the HSI community needs to make the business case to communicate the value proposition of HSI in lifecycle cost reduction to the system development community. Third, systems acquisition and systems engineering policies need to be appropriately revised to reflect the inclusion of HSI principles and guidelines.

The specific approaches by which these recommendations can be implemented are as follows. Initially, use case scenarios need to be defined to frame the relevant contexts for the system acquisition and engineering communities. Next, a flexible, open, process-oriented, systems engineering tool (preferably in use within the DoD) with library facilities needs to be selected. This tool can serve as a convenient starting point for consolidating human considerations and incorporating HSI processes into the software and systems engineering lifecycles. The tool should support multiple lifecycle models (e.g., incremental prototyping, evolutionary development, etc.). The tool needs to incorporate a library of principles from the behavioral and social sciences, as well as from human factors engineering. In this regard, the key issues identified in this paper need to be addressed along with their impact on performance, cost, and schedule. Finally, an end user oriented front-end should be provided to the tool to avoid the need for an intermediary. With such a methodology and toolset, it will eventually become possible to convey the value proposition of addressing HSI considerations early and throughout the software/system lifecycle to the system acquisition and engineering communities, while also assuring end user acceptance of the tool. ◆

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