

Designer-Centered Design in the Field of Artificial Intelligence: AI as a Workforce Issue

Robert R. Hoffman
Institute for Human and Machine Cognition

October 2021

In this essay I discuss an entailment that Human-Centering has for workforce issues. I put this in relief by comparing Human-Centered design with what has been called "Designer-Centered" design (DCD) (Neville, et al., 2008). A primary focus of a great deal of technology development activity is to create the new computational aids. Technology design and development commence even during the program proposal phase, during which notional computational architectures are envisioned, ones that are supposed to be solutions of great promise. But because the technologists "jump in," they are not prepared up-front with input from cognitive systems engineers, and thus can base their envisioned technologies on limited notions of the cognitive work.

Designer-Centered Design

Perhaps the most frequent justification given for the injection of more technology into work systems is the idea that the technology will off-load the human's work load and result in cost savings due to a workforce reduction. The evidence shows that this is not the case. New technologies demand effort at learning and re-learning; they create new tasks and responsibilities; they engender new forms of error and new cognitive demands (Hoffman, et al., 2018). They create "automation surprises" that lead to mistrust (Bainbridge, 1983). While the insertion of automation may result in some manpower reductions, they require more people who are trained to higher levels of technological expertise.

The military's growing body of experience shows that autonomous systems don't actually solve any given problem, but merely change its nature. It's called the autonomy paradox: The very systems designed to reduce the need for human operators require more manpower to support them (Blackhurst, Gresham and Stone, 2011, p. 20).

In a recent review article, Miller, Howe and Sonenberg (2017, p. 1) said:

A major reason why software is often poorly designed (from a user perspective) is that programmers are in charge of design decisions, rather than interaction designers. As a result, programmers design software for themselves, rather than for their target audience... (p.1).

This illustrates the "trap" of Designer-Centered Design (Neville. et al., 2008): Even smart and well-intentioned people, even ones having prior experience working in the domain, can wrongly assume what the end-user needs. This trap has been discussed frequently, for example with reference to the lack of rigor in usability analysis: "*The road to user-hostile systems is paved with designers' user-centered intentions*" (Hoffman, Klein and Laughery, 2002, p. 73). The trap of DCD has had a wide impact, shaping the technology Research and Development.

On the human-centered side of the fence, DCD It has been the whipping post for advocates of a host of approaches that are oriented to sociology or psychology: Human-Centered Design: Work-Oriented Design, Contextual Design, Customer-Centered Systems, Participatory Design, User-Centered Design, Use-Centered Design, Client-Centered Design, Decision-Centered Design, and more besides (Hoffman, et al., 2002). These are all reactions against DCD and are pretty much making the same pleas.

A main trap engendered by the DCD approach is the failure to properly engage with end-users. While many development projects lay claim to involving end-users in the design process, that involvement typically comes after the AI systems have been envisioned, architected, and created. Cognitive systems engineers have implored the computer science community—for decades—to involve end-users throughout the process, and not just brought in at the end to provide some commentary (Hawley, 2011; Hoffman, Deal, Potter and Roth, 2010). More often, what one sees is the "*... automation of functions by designers and subsequent implementation by users without due regard for the downstream consequences for human performance*" (Hawley, 2011). In his 1999 Presidential Address to the Human Factors and Ergonomics Society, Ohio State University Professor David Woods said that human factors analysis had been relegated to merely "sweeping up behind the parade."

Lessons Learned and Forgotten

Through the 1980s and culminating in the late 1990s, the shortcomings of Designer-Centered Design came to be widely recognized. A 1995 U.S. Department of Defense study estimated that 46% of DoD-funded system development efforts resulted in products that were delivered but not successfully used, and 29% of the funded efforts never even produced a product (cited by Leishman and Cook, 2002). The U.S. Internal Revenue Service spent \$4 billion dollars on a decision support system that, in the words of an IRS official, "does not work in the real world" (Marketplace, January 31, 1997). Well-known system development disasters include the London emergency dispatch system released in 1993 (e.g., Finkelstein and Dowell, 1996) and the U.S. Air Traffic Control system upgrade (Carr and Cone, April 8, 2002). The U.S. Federal Bureau of Investigation spent \$170 million on its Trilogy Information Technology modernization program, a problem-riddled effort resulting in software tools that did not support the true cognitive work of analysts (Eggen, 2005; Goldstein, 2005), which the report disguised by referring to "operational needs" (McGraddy and Lin, 2004).

All of these, and other decades-old cases pointed to the neglect of human considerations during the development of complex human-machine systems.

Experience had shown that devices that are designed according to the 'design-then-train' philosophy... force users to adapt to the system. The user is entangled with the system terminology and jargons that are the designer's view of the world (Ntuen, 1997, p. 312).

The song has remained largely the same.

The Way Forward

The process of system development and evaluation is actually a large-scale psychological experiment, with the technology wrapped in it. In traditional psychological research reports, there is a Methods section and within that are a number of subsections, including one that is just on the "Materials and Equipment." While the primary investment by the sponsor is in the technology, experimentation is necessary to improve and validate the technology. In other words, all of the sponsor's investment is packaged into just one corner of a larger picture. And without empirical data that illuminates that larger picture, the investment is at risk.

The design of AI systems is more than software engineering. In fact, it is a psychological endeavor. The design of interfaces, visualizations, workflows, etc. requires the consideration of human factors, both cognitive and social. The evaluation of AI systems is more than what is called "validation and verification." In fact, a large scale psychological experiment is necessary to evaluate the functionality and performance of an AI-enabled work system.

Computational technologies are conceived and advertised as systems to help in the conduct of certain specific tasks. But they are technology insertions that will interact with the existing work system and shape and influence that entire work system. They are hypotheses about an "envisioned world," and as hypotheses, they must be developed, refined, implemented and studied using methods of cognitive task analysis and the general methodology of experimental psychology (Woods, 1985, 1998).

Experimental designs, well-formed testable hypotheses, and operationally-defined measures and metrics all have to be constructed as a wrapped package. They cannot be tacked on after the technology is built. And the research can only be done well if it is forged by individuals with a solid background in experimental psychology, methodology, statistics, and psychometrics. Many recent clarion calls have asserted the necessity, and not merely the value, of trans- or multi-disciplinary work. In many venues, the importance of Cognitive Systems Engineering (CSE) and Cognitive Work Analysis (CWA) methodologies have been proclaimed. Miller, Howe and Sonenberg, in an 2017 article about "inmates running the asylum," implored AI researchers:

... to collaborate with researchers and practitioners from social and behavioral sciences, to inform both model design and behavioral experiments (manuscript p.4).

Similarly, Langer, et al., 2021 said:

Notions of understanding and of contextual influences on human processing of information call for input from research disciplines outside of computer science... Insights from psychology are needed to design experimental studies (Langer, et al., 2021, manuscript p.3; see also Doshi-Velez, and Kim, 2017).

Workforce: The Reality and the Prospects

As it turns out, multi- or trans-disciplinary efforts are already happening, albeit in a nascent form. Interviews with a number of highly experienced AI stakeholders (Hoffman, et al., 2021) revealed some interesting cross-disciplinary mixtures. One of the interviewees had risen to the post of System Development Team Leader but had been trained in Cognitive Science as well as Computer

Science. Two other interviewees had been trained in experimental psychology but moved over into applications, becoming Cognitive Systems Engineers and System Developers. Another individual had a background in experimental psychology but moved into Human Factors of AI applications. Yet another individual had been trained in Industrial Systems Engineering but moved into Cognitive Systems Engineering and the role of Systems Developer. Yet another had been trained in mathematics, but was actively involved in system design based on cognitive analysis methods.

For all of these individuals, their experiences and career paths were not as much by design [i.e., curricula with a workforce focus] as by happenstance and personal motivation, as trans-disciplinary requirements were imposed on what had initially been the isolated discipline of technology development.

Collaboration is important, but I make a bolder assertion: Decision making authority in the creation of AI systems must be shared by a Computer Scientist and an Experimental Psychologist (e.g., Cognitive Systems Engineer, Human Factors Engineer). Especially as AI technology advances and expands in scope, there is a National need to develop a cohort of individuals who are:

- (1) trained in the rigors of computer science/AI,
- (2) trained in the rigors of psychological experimentation,
- (3) trained in program and grants management, and
- (4) **and share authority with the computer scientists.**

The creation of this cohort will necessitate much more than just a re-jiggering of graduate curricula. For example, it will require funded internships and Postdoctoral Associateships.

References

- Bainbridge, L. (1983). Ironies of automation. *Automatica*, 19, 775–779.
- Benson, K., and Rotkoff, S. (2011, November). Goodbye OODA Loop: A complex world demands a different kind of decision making. *The Armed Forces Journal*, pp. 26-28.
- Blackhurst, J.L., Gresham, J.S., and Stone, M.O. (2011, October). The autonomy paradox: Why 'unmanned systems' don't shrink manpower. *Armed Forces Journal* (pp. 20-24,40).
- Carr, D. F. and Cone, E. (April 8, 2002). Can FAA Salvage Its IT disaster? *Baseline Magazine*. [<http://www.baselinemag.com/article2/0,1540,656862,00.asp>]
- Cooper, A. (2004). *The inmates are running the asylum: Why high-tech products drive us crazy and how to restore the sanity*. Indianapolis, IN: Sams Publishing.
- Deal, S. V., and Hoffman, R.R. (2010, March/April). The Practitioner's Cycles, Part 1: The Actual World Problem. *IEEE Intelligent Systems*, pp. 4-9.
- Doshi-Velez, F., & Kim, B. (2017). A Roadmap for a Rigorous Science of Interpretability. *ArXiv Preprint ArXiv:1702.08608*. Retrieved from [<https://arxiv.org/abs/1702.08608>]
- Hawley, J.K. (2011, February). Not by widgets alone. *Armed Forces Journal* [<http://armedforcesjournal.com/not-by-widgets-alone/>]

EGGEN, D. (June 6, 2005). FBI pushed ahead with troubled software. *Washington Post*. [https://www.washingtonpost.com/wp-dyn/content/article/2005/06/05/AR2005060501213.html]

Finkelstein, A. and Dowell, J. (1996). A comedy of errors: the London Ambulance Service case study. *Proceedings of the 8th International Workshop on Software Specification and Design IWSSD-8*, pp. 2-4.

Goldstein, H. (2005, September). Who killed the virtual case file? *IEEE Spectrum* [https://spectrum.ieee.org/who-killed-the-virtual-case-file].

Hoffman, R.R., Klein, G., Mueller, S.T., and Tate, C. (2021). "The Stakeholder Playbook." Technical Report to the DARPA Explainable AI Program.

Hoffman, R.R., Deal, S.V., Potter, S., and Roth, E.M. (2010, May/June). The Practitioner's Cycles, Part 2: Solving envisioned world problems. *IEEE Intelligent Systems*, pp. 6-11.

Hoffman, R.R., Sarter, N., Johnson, M., & Hawley, J.K. (2018). Myths of automation and their implications for procurement. *Bulletin of the Atomic Scientists*, 7 (4), 255–261. <https://doi.org/10.1080/00963402.2018.1486615>

Hollnagel, E. and Woods, D. D. (2005). *Joint cognitive systems: Foundations of cognitive systems engineering*. Boca Raton, FL: Taylor and Francis.

Leishman, T. R., and Cook, D. A. (2002). Requirements risks can drown software projects. *Crosstalk*, 15, 4-8. Retrieved from [http://www.stsc.hill.af.mil/crosstalk/].

Lyle, D. (201, December). Looped back in: We've been using the wrong OODA picture. *The Armed Forces Journal*, p. 32.

Marketplace. (1997, Jan). *Marketplace for January 31st, 1997*. National Public Radio.

McGraddy, J. C. and Lin, H. S. (Eds.) (2004). "A Review of the FBI's Trilogy Information Technology Modernization Program." Report from the Committee on the FBI's Trilogy Information Technology Modernization Program, Computer Science and Telecommunications Board Division on Engineering and Physical Sciences, Washington DC: National Academies Press.

Miller, T., Howe, P., and Sonenberg, L. (2017). Explainable AI: Beware of inmates running the asylum. [arXiv:1712.00547]

Neville, K., Hoffman, R.R., Linde, C., Elm, W.C. and Fowlkes, J. (2008, January/February). The procurement woes revisited. *IEEE Intelligent Systems*, pp. 72-75.

Hoffman, R.R., Roesler, A. and Moon, B.M. (July/August 2004). What is design in the context of Human-Centered Computing? *IEEE Intelligent Systems*, pp. 89-95.

Dekker, S.W.A., Nyce, J.M. and Hoffman, R.R. (March-April 2003). From contextual inquiry to designable futures: What do we need to get there? *IEEE Intelligent Systems*, pp. 74-77.

Hoffman, R.R., Feltovich, P.J., Ford, K. M., Woods, D. D., Klein, G. and Feltovich, A. (July/August 2002). A rose by any other name... would probably be given an acronym. *IEEE Intelligent Systems*, 72-80.

Hoffman, R.R., Klein, G. and Laughery, K.R. (January/February 2002). The state of cognitive systems engineering. *IEEE Intelligent Systems*, pp. 73-75.

Hoffman, R.R. and Woods, D.D. (2011, November/December). Beyond Simon's slice: Five fundamental tradeoffs that bound the performance of macrocognitive work systems. *IEEE Intelligent Systems*, pp. 67-71.

Johnson, M. and Vera, A.H.(2021, Spring). No AI is an island: The case for teaming intelligence. *The AI Magazine*, pp. 17-28.

Klein, G., Ross, K.G., Moon, B.M., Klein, D.E., Hoffman, R.R., and Hollnagel, E. (May/June, 2003). Macrocognition. *IEEE Intelligent Systems*, pp. 81-85.

Langer, M. (with 7 others). What Do We Want From Explainable Artificial Intelligence (XAI)? A Stakeholder Perspective on XAI and a Conceptual Model Guiding Interdisciplinary XAI Research. *Artificial Intelligence*, in press. [arXiv:2102.07817]

Ward, P., Hoffman, R.R. Conway, G.E., Schraagen, J.M., Peebles, D., Hutton, R.J.B., & Petushek, E.J. (Eds.) (2018). *Macrocognition: The science and engineering of sociotechnical work systems*. Frontiers Media. [doi: 10.3389/978-2-88945-418-1]

Woods, D.D. (1985, Winter). Cognitive technologies: The design of joint human-machine cognitive systems. *The AI Magazine*, 86-92. [<https://doi.org/10.1609/aimag.v6i4.511>]
Woods, D.D. (1998). Designs are hypotheses about how artifacts shape cognition and collaboration. *Ergonomics*, 41, 168-173.