Human Systems Integration of Human-AI Teaming

Guy André Boy
CentraleSupélec (Paris Saclay University) & ESTIA Institute of Technology
Gif-sur-Yvette & Bidart, France
guy-andre.boy@centralesupelec.fr orcid.org/0000-0002-0497-7949

***Abstract*— Nowadays, human systems integration (HSI) requires expansion, considering the inclusion of artificial intelligence (AI) in most critical systems. Consequently, systems engineering and AI must be developed in concert with the new perspective of human-AI teaming (HAT). This article attacks this endeavor by considering human factors such as situation awareness, decision-making, and risk-taking. It raises issues of function allocation, design and operations flexibility, and incremental design of technology, organizations, and people's competencies. More specifically, it brings the major issue of certification impossibility and the need for qualification of AI systems, shifting these systems from tools to partners.**

Keywords—human-AI teaming, human systems integration, trust, collaboration, operational performance.

I. Introduction

Artificial intelligence (AI) [24] and human-AI teaming (HAT) [25] have been coined and investigated a long time ago. HAT [1] should be explored further from a human systems integration (HSI) perspective, specifically model-based HSI. This paper attempts to integrate several pieces of work done in HSI toward this end [2,3,4,13,14,15,16]. HAT is closely associated with the concept of autonomy. Consequently, the term "Human Autonomy Teaming," also known as HAT, is currently used in the defense sector [5]. The concept of autonomy requires further investigation and a more formal physical and cognitive systemic representation supporting more detailed and meaningful analysis, specifically on situation awareness issues [6], decision-making, and risk-taking. A new question is: "To what extent should the machine be considered a tool or a partner?"

HSI is defined as the intersection of Systems Engineering (SE), Human Factors and Ergonomics (HF/E), and Information Technology [9]. Along these lines and beyond the current trend of combining SE and AI [8], an even more vital need emerges to incorporate AI and HSI. Therefore, we need to examine HSI based on a consistent definition of a system where humans and machines can be considered together using a homogeneous representation that supports agent-oriented system modeling [13]. More specifically, HAT analysis, design, and evaluation require the development of an appropriate ontology based on HSI and AI principles and concepts, such as HSI-based systems and AI-based agents [4,7].

This paper will raise control, responsibility, autonomy, and trust issues [10] in air and space power. AI allows the execution of tasks that usually require human intelligence, such as perception, conversation, and decision-making [11]. AI includes many technologies and applications, such as knowledge-based systems, vision, speech, natural language processing, robotics, machine learning, and planning. If machine autonomy is a contemporary trend, human autonomy remains a significant concern when people must solve problems in unexpected or unknown situations using appropriate human skills, knowledge, technologies, and organizational setups. Underlying concepts, methods, and tools are currently being developed by the FlexTech Chair [3,4], where we develop FlexTech functions (technology for flexibility), AI-based or not, to support problem-solving, whether in expected or unexpected situations.

II. Human Systems Integration

A. Procedures, Automation, and Problem-Solving

Procedures-following and automation monitoring are usually excellent solutions in expected situations (Fig. 1). Still, they can be counterproductive and even dangerous in unexpected situations that require flexibility, autonomy, more profound knowledge, and problem-solving skills [14]. We then need to analyze the automation-autonomy distinction to address this flexibility challenge. For a long time, we automated machines, often without considering the unexpected situations that were implicitly left to the end-users, who had no choice but to solve them, often without appropriate resources. It is time to address this gap in evolving from rigid automation to flexible autonomy, where autonomy has become a human-machine concept. Indeed, we have massively automated machines during the 20th century. However, AI-based automation, which leads to increasingly autonomous machines, still needs to mature and requires more fundamental and applied research efforts (e.g., concurrently addressing technology, human, and organizational readiness levels [4]).

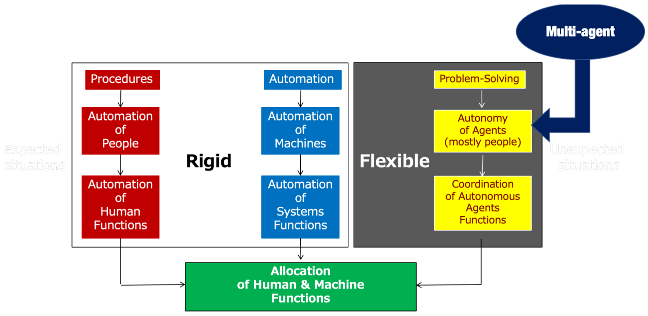

Fig. 1. Procedures, automation, and problem-solving: Rigid vs. Flexible.

B. Human and Machine Systems of Systems Specifications

In this context, it becomes relevant to consider an agent as an agency of agents [12], where agents are humans or machines increasingly equipped with artificial intelligence (AI) algorithms. Agents can identify a situation, decide, and plan appropriate actions. It is interesting to realize that **multi-agent representations developed in AI are very similar to systems of systems (SoS) designed in SE**. Consequently, these AI and SE approaches must be cross-fertilized. Indeed, the ever-increasing interconnectivity makes such a multi-agent/SoS approach even more necessary.

Command and control (C2) systems are now integrated with user interfaces, and, more generally, interconnectivity has become a real support to agency operations requiring human-centered systemic integration [4]. At this point, defining what we mean by a system becomes crucial. Several definitions have been proposed. Most people think of a system as a machine. However, when doctors talk about the cardiovascular system, they are talking about a **representation** of a human organ that allows blood to

979-8-3503-1579-0/24/$31.00 ©2024 IEEE

circulate throughout the body, not a machine in the mechanical sense. Social scientists talk about socio-cultural systems. Here again, they speak of representations [4].

Whenever new life-critical machines, such as human-crewed or uncrewed aircraft or spacecraft, are developed, they must be certified to ensure safe, efficient, and comfortable operations. Therefore, establishing metrics to evaluate and validate them is crucial. HAT-dedicated metrics will be presented from the perspective of machines considered partners, specifically operational performance, trust, and collaboration. Although a possible future aviation system will illustrate the following development, we will discuss the role of humans and organizations within the scope of more generic life-critical systems based on the current PRODEC method developed [3,13,23], including authority sharing. PRODEC is a scenario-based design method combined with human-in-the-loop simulations and activity analysis. The conclusion will review the recent HAT theoretical and practical results and open perspectives.

III. Function allocation: looking for flexibility

A. Automation, Interaction, and Augmentation

There are three ways of implementing function allocation among humans and machines, associating design and operations-related processes [7]: substitution with automation, amplification with interaction, and speculation with augmentation.

Automation functions have existed for a long time, based on automatic control theories (e.g., in aviation, autopilots that can follow a heading, a speed, an altitude, and so on; cruise control on automobiles). Skill-based human cognitive functions have been transferred to machines. The problem is that these functions, defined in specific contexts, lead to rigid automation (Fig. 1).

Human-computer **interaction** functions could amplify various human cognitive functions, including human memory capacity, shortcuts, heavy calculations, and search algorithms that enable finding appropriate information in context, where context is incrementally learned by the machine from previous interactions, for example [3].

Speculation is directly associated with **augmentation** at operations time. Engineers designed aircraft functions that provide flying capabilities to humans. Not only did we understand that thrust and lift can make us fly, but we also found the appropriate means of propulsion and lift.

B. Evolution of Human-Machine Function Allocation

It is essential to understand the evolution from HF/E to Human-Computer Interaction (HCI) to HSI communities in the light of the triptych (automation, interaction, augmentation). HF/E was born from problems that needed to be solved in industry after World War 2, where machines were essentially mechanical and incrementally automated. Automation became a real issue because people had to adapt to it. Substituting a human function for a machine function created new human functions that engineers did not necessarily anticipate. HF/E specialists had to help fix these issues. Automation increases safety, efficiency, and comfort in well-defined operational contexts but also operational rigidity (Fig. 1).

At the beginning of the 1980s, computers started to be used extensively, which created new issues related to HCI. A new community was designed to study these issues. People could do more things using computers because software amplified their capabilities. However, these new machine functions still needed to remove rigidity in operations. Indeed, machine functions were designed in specific contexts, even if they were highly interactive. It took a long time to realize that flexibility requires functions, such as the “undo” function, to solve problems without procedures. This type of function Is denoted “**FlexTech.**” [22]

If an aircraft augments human capabilities, flying a fixed-wing plane, for example, is far more rigid than what birds can do. Birds are, therefore, more flexible and autonomous than what people can do with an aircraft. This is due to their structure of structures (i.e., anatomy) and functions (e.g., 3D perception, feeling of the air). The symbiosis between these structures and functions provides them with appropriate flight capabilities.

Consequently, more speculations should be carried out (e.g., stability as a crucial flight function). Quadcopters have four engines (i.e., agents) that ensure enhanced stability, providing pilots more operational flexibility and autonomy. This example shows that a well-articulated multi-agent function allocation is a solution for flexibility.

IV. From rigid automation to flexible autonomy

During the last four decades, we have proved that operations procedures and automation can successfully support the control and management of life-critical systems. Automation is usually thought of as the automation of machine functions (Fig. 1), and operation procedures can be considered automation of people [7].

Problems come when unexpected situations occur, and rigid assistance (i.e., procedures and automation) may no longer work because operations procedures and automation are out of their validity contexts. Human problem-solving is usually at stake. Instead of following procedures and monitoring automation, people need well-coordinated, multi-agent expert support. The Apollo 13 successful failure[1] is an excellent example of that.

In addition, function allocation cannot be considered a static process. It is highly dynamic, and systems should be flexible enough to be modified incrementally. A good mastery of the tryptic Technology-Organizations-People denoted as the TOP model [2] and collective preparedness of the human and machine agents at stake will improve flexibility [3].

Technological, organizational, and human flexibility must be considered during design and operations. Design is an iterative process that requires many changes, considering the TOP model framework toward three perspectives: HSI, case-based reasoning, machine learning, and visualization techniques that contribute to improving situation awareness.

HSI involves leveraging individuals' and corporate accumulated experience and expertise within a system to enhance performance. Adjustable autonomy should be based on experience, acquired incrementally through many try-and-

[1] www.nasa.gov/missions/apollo/apollo-13-the-successful-failure

979-8-3503-1579-0/24/$31.00 ©2024 IEEE

error activities. A positive experience is as necessary as a negative experience. If incidents and accidents are well documented and can serve as valuable data for learning, we should focus even more on positive experiences. These experiences should be stored in knowledge-based systems (i.e., repositories of structured knowledge to assist in decision-making processes).

Case-based reasoning [17] involves solving new problems based on solutions to similar past problems. These approaches can be highly effective in HSI scenarios, especially when combined with supervised machine-learning techniques to learn from historical data. Situation awareness refers to understanding elements in the environment within a volume of time and space, comprehending their meaning, and projecting their status shortly. Intelligent visualization techniques, often powered by deep learning algorithms, enhance situation awareness by presenting complex data comprehensibly to human operators.

Machine Learning (ML) and, even more importantly, Deep Learning (DL) have become dominant over the last few years [21]. ML can be very interesting within our flexible autonomy endeavor. ML algorithms support eliciting patterns, information organization, anomalies, relationship detection, and projection making. They can also help fine-tune how autonomous systems improve task execution using appropriate metrics [7].

Visualization techniques enable complex data to be better understood by people [18,19,20]. Indeed, becoming familiar with a complex system is a critical issue that appropriate static or dynamic visualizations can enhance. Visualization is at the heart of HAT [10].

HAT involves human and machine agents within an infrastructure that can be hierarchical (e.g., conventional army) or heterarchical (e.g., orchestra). The evolution of digital (especially AI) organizations drastically changed people's jobs, going from old army hierarchies to heterarchical orchestra structures and functions [4,15], with musicians, some of them being conductors and composers. More formally, playing a symphony (i.e., a product), the orchestra organization requires five kinds of components:

1. music theory that is the common language (i.e., a framework and vocabulary for collaborative work);
2. scores produced and coordinated by composers (i.e., coordinated tasks to be executed);
3. workflow coordinated by a conductor (i.e., system of systems activity);
4. musicians performing the actual symphony (i.e., the actual system of systems);
5. the symphony audience (i.e., product's end users).

Three transversal dimensions must be added to describe HAT interaction [2]: supervision of agents over other agents interacting with each other, mediation between agents by "mediating" agents, and cooperation among agents that learn from each other through interaction over time.

On the human side,

Autonomy should not be focused on technology only. In cooperation with AI, human autonomy is undoubtedly just as significant, if not more so. From the TOP model perspective [2], we will discuss the independence of designers, engineers, developers, certifiers, maintainers, operators or end-users, trainers, and dismantlers, to name a few. Sometimes, new technology may lead to people losing their jobs, or conversely, new jobs (i.e., functions) should be created. Therefore, a new set of people might be hired (i.e., a new structure should be made within the organization). People have their own human factors issues, such as fatigue, workload, physical and cognitive limitations, and creativity [2]. These are topics for HAT research.

V. Current H.A.T. developments

We are currently working on the PRODEC method that supports the development and operations of sociotechnical multi-agent systems [23]. PRODEC is a scenario-based design method that enables eliciting emergent properties from task, activity, and function analyses, using human-in-the-loop simulation during the whole life cycle of a socio-technical system and, more specifically, at design time. Since humans and AI-enforced machines have physical and cognitive functions, PRODEC is very appropriate to identify and formalize these functions.

This HAT approach has been and is currently tested on various projects and use cases, including the MOHICAN project [16], the management of a fleet of robots on an off-shore oil-and-gas drilling platform, and a future combat air system. We currently learn on HAT from these laboratory and real-world experiences using PRODEC.

Conclusion

This paper was produced to support the IEEE ICHMS 2024 Special Session on Adjustable Human-Autonomy Collaboration and encourage research and innovation that mixes HSI and AI toward technological solutions that help flexibility in operations. Flexible autonomy is mainly needed in abnormal situations and emergencies, where people must solve problems, often not anticipated, and speculate appropriate solutions. This is precisely where AI could be efficient and effective by supplying tools that augment people's capabilities in problem-solving and judgment.

Human-AI teaming (HAT) is sensitive to trust and collaboration [16] that directly impact operational performance, supporting safe, efficient, and comfortable work. This leads to testing HAT reliability, which results from the **co-adaptation of people and machines** (via designers and engineers, as well as trainers and accumulated experience).

Human operators may accept some unreliable situations where the machine fails as long as safety, efficiency, and comfort costs are low (i.e., acceptable degraded modes of operations). However, when these costs become too high for them, the machine is just rejected. This states the problem of product **maturity** [4]. HAT maturity remains a research topic that deserves attention, as AI systems cannot explain what they do and learn, so they can be different from one day to the next. More specifically, AI-intensive machines cannot be considered tools but partners that require qualification tests, in the same way people are qualified for a job. In addition, HAT qualification will have to be continuous during the life cycle of a system.

Along these lines, with increasing AI support, HSI should be based on a concurrent approach to cross-fertilizing technology, organizations, and people's activities (i.e., based on the TOP model). This work is part of the research by the

979-8-3503-1579-0/24/$31.00 ©2024 IEEE

FlexTech Chair at CentraleSupélec (Paris Saclay University) and the ESTIA Institute of Technology.

References

[1] NASEM, *Human-AI Teaming: State of the Art and Research Needs*. National Academy of Sciences, Engineering, and Medicine, Washington D.C. The National Academy Press. https://doi.org/10.17226/26355. 2021.

[2] G.A. Boy, *Human Systems Integration: From Virtual to Tangible*. Miami, FL, USA: CRC Taylor & Francis Press. 2020.

[3] G.A. Boy, 'Model-Based Human Systems Integration.' In the *Handbook of Model-Based Systems Engineering*, A.M. Madni & N. Augustine (Eds.). Switzerland: Springer Nature. 2023.

[4] G.A. Boy, 'An epistemological approach to human systems integration.' *Technology in Society*, 102298 (Open access), Elsevier. https://doi.org/10.1016/j.techsoc.2023.102298. 2023.

[5] J.B. Lyons, K. Sycara, M. Lewis and A. Capiola, 'Human–Autonomy Teaming: Definitions, Debates, and Directions.' *Frontiers in Psychology – Organizational Psychology*. https://doi.org/10.3389/fpsyg.2021.589585. 2021.

[6] M.R. Endsley, 'Situation awareness in future autonomous vehicles: Beware the unexpected.' *20th Congress of the International Ergonomics Association*. Florence, Italy, and Springer Nature. 2018.

[7] G.A. Boy, 'Cross-Fertilization of Human-Systems Integration and Artificial Intelligence: Looking for Systemic Flexibility.' *Proceedings of AI4SE 2019, First Workshop on the Application of Artificial Intelligence for Systems Engineering*. Madrid, Spain. 2019.

[8] T. McDermott, D. DeLaurentis, P. Beling, M. Blackburn and M. Bone, 'AI4SE and SE4AI: A Research Roadmap.' *INCOSE Insight*. March issue. DOI 10.1002/inst.12278. 2020.

[9] INCOSE HSI Primer vol 1, *The Human Systems Integration Primer*. INCOSE Central Office, 7670 Opportunity Rd., Suite 220, San Diego, CA 92111-2222. 2023.

[10] K.E. Schaefer, S.G. Hill and F.G. Jentsch, *Trust in Human-Autonomy Teaming: A Review of Trust Research from the US Army Research Laboratory Robotics Collaborative Technology Alliance*. Springer International Publishing AG, part of Springer Nature (outside the USA), J. Chen (Ed.): AHFE 2018, AISC 784, 102–114. https://doi.org/10.1007/978-3-319-94346-6_10. 2019.

[11] M. Kanaan, *T-Minus AI – Humanity's Countdown to Artificial Intelligence and the New Pursuit of Global Power*. Dallas, Texas, USA: BenBella Books, Inc. ISBN 978-1-948836-94-4. 2020.

[12] M. Minsky, *The Society of Mind*. Simon & Schuster, USA. 1986.

[13] M.E. Miller, J.M. McGuirl, M.F. Schneider & T.C. Ford (2020). System modeling language extension to support modeling of human-agent teams. *Systems Engineering*, 23(5), 519-533.

[14] G.A. Boy, 'Dealing with the Unexpected in our Complex Socio-technical World.' *Proceedings of the 12th IFAC/IFIP/IFORS/IEA Symposium on Analysis, Design, and Evaluation of Human-Machine Systems*. Las Vegas, Nevada, USA. Also, Chapter in *Risk Management in Life-Critical Systems*, Millot P., and Boy, G.A., USA: Wiley. 2013.

[15] G.A. Boy, *Orchestrating Human-Centered Design*. Springer, 2013.

[16] G.A. Boy, and C. Morel, 'The Machine as a Partner: Human-Machine Teaming Design using the PRODEC Method.' *WORK: A Journal of Prevention, Assessment & Rehabilitation*. Vol. 73, no. S1, pp S15-S30. DOI: 10.3233/WOR-220268. 2022.

[17] A. Aamodt & E. Plaza, Case-Based Reasoning: Foundational Issues, Methodological Variations, and System Approaches, *Artificial Intelligence Communications* 7: 1, pp. 39-52 1994.

[18] N. Garcia Belmonte, Engineering Intelligence Through Data Visualization at Uber. (retrieved on July 29, 2019: https://eng.uber.com/data-viz-intel/). 2016.

[19] N. Kruchten, Data visualization for artificial intelligence, and vice versa. (retrieved on July 30, 2019: https://medium.com/@plotlygraphs/data-visualization-for-artificial-intelligence-and-vice-versa-a38869065d88). 2018.

[20] R. St. Amant, C.G. Healey, M. Riedl, S. Kocherlakota, D.A. Pegram, M. Torhola, Intelligent visualization in a planning simulation. Proceedings Intelligent User Interfaces IUI'01). Sante Fe, New Mexico. ACM 1-58113-325-1/01/0001. 2001.

[21] Y. LeCun, Y. Bengio & G. Hinton, Deep learning. *Nature* **521**, pp. 436–444. 2015.

[22] G.A. Boy (2021). *Design for Flexibility*. Springer Nature, Switzerland.

[23] G.A. Boy, D. Masson, E. Durnerin & C. Morel (2024). PRODEC for Human Systems Integration of Increasingly Autonomous Systems. *Systems Engineering Journal*. Wiley, USA.

[24] M. Minsky (1961). Steps toward artificial intelligence. *Proceedings of the IRE*, 49(1), 8-30.

[25] J.C.R. Licklider & W.E. Clark (1962). Online man-computer communication. *AFIPS Proceedings – 1962 Spring Joint Computer Conference*, 113-128.

979-8-3503-1579-0/24/$31.00 ©2024 IEEE