Evolving Relationship between Humans and Machines ⋆

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Abstract: Traditional design typically consists of a master-servant relationship between humans and machines where the human directly controls what the machine will do and when it will do it through an interface. The current archetypical path encompasses moving from informational displays, where the human directly controls the machine based on information displayed, to automation where the human still directs the machine that then caries out the request using predefined set of instructions. Rapid pace of technological advancement makes it possible now, or in a near future, for machines to reach a level of intelligence that enables for systems to execute tasks/missions without predefined specific instructions; thus attaining a status of non-human autonomous agents. Now the course of human-machine interface technology changes from an information system to automation to an autonomous agent—essentially moving from a master-servant relationship to teammates. This paper discusses these changing relationships and challenges associated with progressing from a master-servant relationship with technology to more of an equal teammate. Examples of this progression includes current work encompassing rotorcraft noise minimization for urban air mobility.

Keywords: Human-machine interface, supervisory control, master-slave systems, active noise control

1. INTRODUCTION

Traditional system design encompassing human operators and machinery typically consists of a master-servant relationship between humans and machines. Humans specify commands the machine will perform and when it will do these prescribed commands through an interface. The current archetypical path encompasses moving from informational displays to automation. Within the aviation realm, the alerting system is an informational display. Typically a caution or warning message is displayed when sensors detect out-of-bound parameter(s) indicating a system failure. The pilot then uses that information to look up appropriate checklists which he then completes. For automation, a common example is the aircraft's autopilot that moves control surfaces accordingly to carry out higher-level command such as "ascend at 500 feet per minute."

Rapid pace of technological advancement makes it possible now, or in a near future, for machines to reach a level of intelligence that enables systems to execute tasks or missions without specific predefined instructions; thus attaining a status of non-human autonomous agents. Choe et al.'s (2016) and Puig et al.'s (2015) work on time coordination of multiple unmanned aircraft, and Widdowson et al.'s (2018) and Marinho et al.'s (2016) virtual reality research on small unmanned aircraft around humans are examples of autonomous agent behavior specified with high level goals rather than predefined specific instructions. Self-aware vehicle concept with adaptive mission management incorporating autonomous control across vehicle subsystems, situation awareness, intelligent contingency management, decision making regarding given mission and its execution, introduced in Gregory et al. (2016), to enable an intelligent autonomous vehicle and research building upon this concept is another example of machines moving beyond tightly prescribed actions.

Now the course of human-machine interface (HMI) technology is rapidly evolving from an information system to automation to an autonomous agent—essentially moving from a master-servant relationship to teammates. This paper discusses these changing relationships and challenges associated with progressing from a master-servant relationship with technology to more of an equal teammate. An example of this progression is the current work encompassing rotorcraft noise minimization for urban air mobility.

2. INFORMATION SYSTEMS

A typical first step for integrating new technology is to provide information to the human operator so that he

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may appropriately control the system. Therefore, the system must provide adequate information that appropriately maintains the situation awareness of the human controller. This involves, at a minimum, providing information to the human operator about the current situation. To better support the human controller, interfaces now typically provide fused data to aid the human in comprehension of the current situation and some predictive capabilities about the future. This is Endsley's (1995) situation awareness model.

To provide this information to the human operator, ecological interface design principles (see Vicente and Rasmussen, 1992; Vicente et al., 1995; Vicente, 1996) are often employed, especially in the age of graphical user interfaces (GUI). These design principles enable constraints and relationships in the system to be evident to the operator; thus increasing situation awareness. However, the execution of a function based on obtained information resides with the human operator; the human has direct control (Fig. 1).

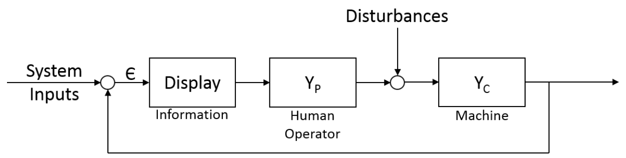

Fig. 1. Information system block diagram where human operator has direct control of machine

3. AUTOMATION

As the information proves useful and in the push to increase efficiency, actions the human operator performs based on provided information are automated as control capabilities present themselves. However, execution authority resides solely with the human controller in that the human authorizes task specific functions to the automation which performs them in tightly prescribed and predictable ways (Fig. 2).

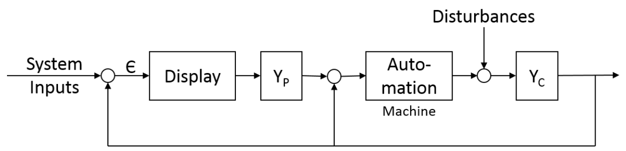

Fig. 2. Automation block diagram where human operator has executable control of machine

Automation executes tasks specified by the human operator. In this case the interface typically adds commands to tell the automation what to execute rather than redesigning the whole interface based on a new role, which should add consideration of the different function allocation between the human and the automation in addition to the possibly changed information needs of the operator. Function allocation between the automation and the human operator typically is determined by what the automation can do with the rest of the functions relegated to the human operator to fill in the gaps irrespective of the human operator's capabilities. This frequently results in degraded overall performance and piecemeal system design.

This type of design that adds automation in a piecemeal fashion without reconsidering the system as a whole is driven by a number of factors, among them cost and recertification, but it introduces its own costs, often hidden or latent. When the interface and information needs of the operator are not fully considered, this often results in automation surprises—"What's it doing now?" syndrome (see Sarter and Woods, 1992, 1995; Sarter et al., 1997). An additional issue that often arises is the lack of communication from the automation. This results in "silent co-pilots" as described by Kirlik et al. (2017). To the human operator, these "silent co-pilots" typically fail abruptly (for example, see Wilson, 2012). This often results in systems not being used, thus eliminating potential efficiencies, or in serious incidents or accidents.

A change in design paradigm is needed when moving from an information system to automation because the relationship between human and machine changes; however, this is rarely done. These changes should include moving from manual control, even in reversionary mode, to more of a manager of the function the automation is taking over. This requires different information and thus a different interface for the manager in addition to changes in function allocation. Additionally, there are requirements on automation itself. For the designed function, automation must demonstrate reliability and predictability as well as graceful performance degradation as it approaches the prescribed bounds of its authority, unlike current commercial aircraft autopilot that disconnects abruptly handing the aircraft in an unusual attitude to potentially situationally unaware unsuspecting pilot. Moreover, the approach of authority bounds must be communicated in a timely and appropriate manner to the operator.

4. AUTONOMOUS AGENTS

Advances in machine learning—especially in vision algorithms and perception—and robotics are allowing movement from "dumb" autonomy to "smart" autonomous agents that are able to make and carry out decisions within a defined solution space without a human operator's input. In these instances, the autonomous agent becomes part of a team with humans (Cronk, 2012; Ensor, 2014) but these autonomous teammates are still learning to deal with humans (Richtel and Dougherty, 2015; Fairley, 2017).

4.1 Teammates

In teams, members have particular jobs or tasks they are in charge of but may also be cross-trained so that any teammate may pick up the tasks of another in case of task overload or incapacity. Task function allocation is optimized based on human capabilities. This will need to occur in teams consisting of both humans and machines, especially as machines become more intelligent.

As with moving from information systems to automation, a change in design philosophy is needed when moving from automation to autonomous agents. Now the autonomous agent is carrying out a separate task. But to be an effective team member, the autonomous agent must also be cross-trained, within its capabilities, which then requires fluid function allocation in the team when the need arises. With fluid function allocation, there will be bidirectional task assignment from human to machine and vice versa.

4.2 Characteristics of Good Teammates

Communication. Communication is core to a successful team. This will ensure that all members of the team, whether human or machine, have the same understanding of the goals, objectives, current situation, and plans. For human team members, understanding machine decisions is paramount. Essentially, machine behavior needs to be transparent to the human teammates. An approach to understanding, developing, and maintaining communication is the Army Research Laboratory situation awareness-based transparency (SAT) model (Chen et al., 2014), which mirrors Endsley's (1995) situation awareness model. The first level consists of basic information such as purpose, process, and current performance and status. The second level consists of rationale or the agent's reasoning process which may include environmental and other constraints. The third level consists of outcomes and includes projections of future outcomes, uncertainty, likelihood of success, and performance history.

Trust. Teammates must trust one another to make correct decisions and to carry out tasks. This is usually developed while training and working together when team members learn to predict one another's actions. Thus, trust is based on experience and predictable behavior. Trust has traditionally been subjective but research is now ongoing looking at humans developing trust in autonomous agents who display possible outcomes and decision making (for example, see Beller et al., 2013; McGuirl and Sarter, 2006; Verberne et al., 2012). Additionally, there is some preliminary research in trying to objectively measure trust (Trujillo, 2018). Others are now using techniques to correlate trust with physiological responses by linking human arousal with autonomous agent behavior in proximity to humans (Widdowson et al., 2018; Marinho et al., 2016).

Sacrifice. A highly functional team incorporates individual teammate sacrifice. This is a willingness to sacrifice own goal optimization to allow mission success. In other words, local agent optimization is sacrificed for global mission optimization (Gregory and Trujillo, 2016).

4.3 Other Considerations

Autonomous agents must be able to deal with conditions that may not have been foreseen during the design or every possible combination of actions considered. This implies that autonomous agents must be learning agents by necessity. This raises an important challenge—how to assure appropriate actions within the boundaries of allowed authority. As the autonomous agents become more intelligent their tasks will become more sophisticated and safety critical; thus, making assurance a critical, though not exclusive, part of acceptance.

5. NOISE EXAMPLE

5.1 Noise Information Display

A new system starting down this design path involves providing helicopter pilots with output from a real-time helicopter noise algorithm so that the pilot can decrease ground noise annoyance. Greenwood et al. (2015) has developed an algorithm that indicates current noise footprint based on helicopter type, attitude, and external conditions such as wind. Work is now ongoing to provide a helicopter pilot real-time information about his noise footprint. Before development of this algorithm, helicopter pilots used rules of thumb depicted by a "fried egg" plot (Fig. 3) (Helicopter Association International Fly Neighborly Committee, 2007).

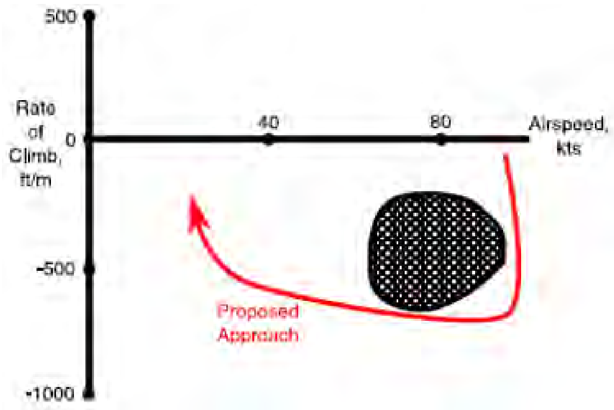

Fig. 3. "Fried egg" plot depicted noise footprint for helicopter (from Greenwood, 2017)

With Greenwood's noise algorithm that considers real-time blade vortex interaction and helicopter attitude, a display indicating actual noise footprint on the ground and changes in helicopter attitude to decrease this footprint is now possible. Here, the team consists of the algorithm with its associated displayed information and the pilot who acts on this information. Function allocation is not a concern because the algorithm only provides information. This information must be conveyed such that the helicopter pilot understands the noise footprint projection on the ground and current noise levels based on the helicopter's attitude. It should also inform in real time attitude changes needed to decrease the noise on the ground. This incorporates all aspects of the SAT model. As long as the noise footprint changes as expected with helicopter attitude, trust is maintained in the system. Because this is only an information system, sacrifice does not factor in because the helicopter pilot has sole authority in changing the helicopter's attitude. Therefore, for an information system, communication and trust are the primary factors in the system.

Other consideration for an information display for helicopters include several operational aspects. For example, ground noise is a factor primarily when the helicopter is close to the ground. When close to the ground, helicopter pilots are looking out, not looking in at their instrument panel. This forces the options for the information display to be a small succinct display, a helmet-mounted or head-up display, tactile or aural cues, or a training aid that is used between flights. Currently a training aid is being developed that will also test the visual implementation of information (Fig. 4 on the next page).

With the noise algorithm, piloting commands are available to decrease this noise footprint. This initial information

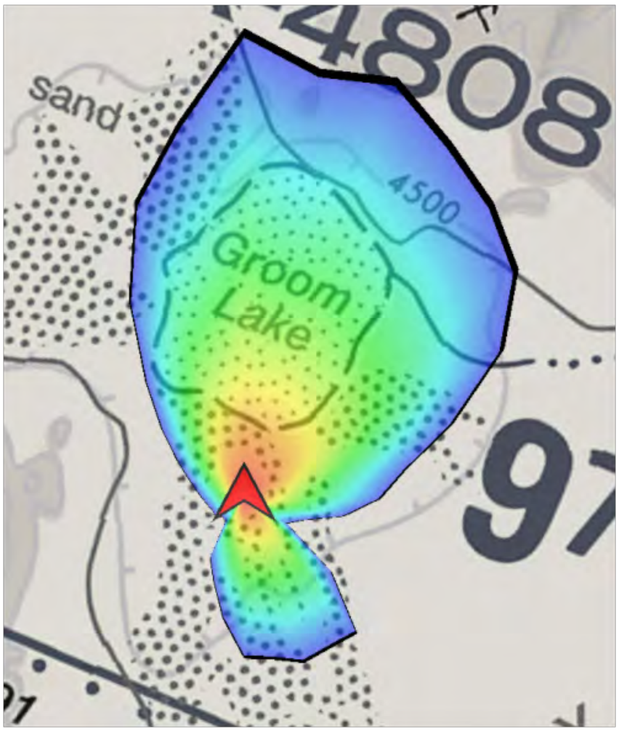

Fig. 4. Example Real-Time Helicopter Noise Footprint (from Greenwood, 2017)

display will indicate to the helicopter pilot suggested commands to decrease noise footprint such as "laterally accelerate and/or ascend" (Greenwood, 2017). With these commands comes the possibility of automating them.

5.2 Noise Automation

There is ongoing work to further automate noise reduction for both helicopters and other multi-rotor vehicles envisioned for Urban Air Mobility (for example, see Gregory et al., 2018). In particular, for multi-rotor vehicles, noise abatement is multi-tier control problem that is tightly coupled to a particular configuration. Different vehicle configurations are more or less amenable to noise control. Given a configuration, noise abatement becomes part of close-loop control of vehicle flight/propulsion system. At the next tier, noise control is part of vehicle trajectory. For automation, the pilot receives the suggested trajectory and makes the final decision. Figure 5 illustrates the difference a noise constraint can make in trajectories for a minimum time mission. Given the pilot's understanding of priorities, either can be selected and automatically flown.

Designing a system where automation can implement a set of instructions now requires a different function allocation scheme where the human is moving more towards being an operator rather than directly controlling a vehicle. Therefore, in the above example, function allocation roles are fairly static—the automation flies the trajectory once the operator chooses which one to follow. This will only change when the operator behaves more as a pilot—*i.e.*, taking manual control—and the automation becoming an information display. These reversionary modes must be taken into consideration in the design but the relationship

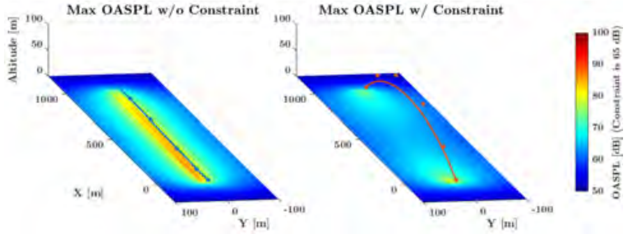

Fig. 5. Minimum time trajectory for a single vehicle without and with acoustic constraint at a single observer location. Relative noise level is provided by the temperature map.

between the human and the automation is still a master-servant relationship.

The automation must still communicate to the operator the possible trajectories and the information provided should also indicate the reasoning behind various trajectories (*e.g.*, minimum time, minimum distance) and a projection of whether various constraints will be met at the end state. This cost function is a low level of sacrifice on the part of the automation. In addition to minimum time (Fig. 5), mission objective may require minimum energy expenditure as the performance metric. Figure 6 illustrates the difference between vehicle flying at constant speed with and without noise constraints. Again, in this case, the pilot has options on which trajectory to select. If the algorithm is consistent in providing feasible trajectories once a performance metric is selected, it becomes trusted and under less scrutiny by the pilot. Trust is then increased in the system as the operator uses the automation and it performs as expected—such as minimizing noise while arriving on time. Another consideration is that the trajectories must be achievable. If they are not, trust in the system is lost with the possibility of the system becoming suboptimal because the operator may be more prone to manually controlling the vehicle.

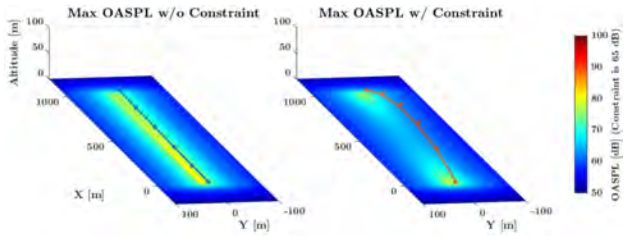

Fig. 6. Constant speed trajectory for a single vehicle without and with acoustic constraint at a single observer location. Relative noise level is provided by the temperature map.

5.3 Noise Autonomy

The urban air mobility market, to be economically feasible and pervasive, requires autonomous vehicles carrying people or cargo. In addition to autonomous flight, noise is one of the major barriers. At the mission level multiple, potentially contradictory, requirements must be considered. These include mission performance (*e.g.*, travel time), energy consumption, dynamic noise signature, and restricted air space. Even under autonomous flight this is where human-machine teaming comes into consideration.

The human-mission manager or dispatcher sets the priorities among the various constraints—*i.e.*, determines the cost function—while onboard mission management system (MMS) optimizes the route under the specified, potentially dynamic, constraints, mitigates any failures and provides tactical mission replanning if necessary. The autonomous MMS would be in communication with the human dispatcher providing updates, receiving new priorities or providing suggested changes based on potential vehicle safety impacts.

In autonomous flight the machine selects the appropriate cost function for the path generation algorithm based on the priorities specified by the dispatcher. The technology is built on previous pilot-automation interactions and justifiable trust, in addition to the rigorous certification process. An example multi-objective trajectory is presented in Fig. 7 illustrating a path for minimum time and energy, conflicting performance, with and without noise constraints. Such algorithms provide an illustration of building blocks to enable assured autonomous flight and new relationship between human and machines that would result from it.

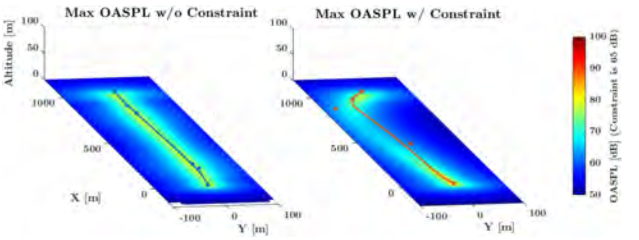

Fig. 7. Minimum energy and time trajectory for a single vehicle without and with acoustic constraint at a single observer location. Relative noise level is provided by the temperature map.

6. CONCLUSION

As machines become more intelligent and can performance more sophisticated functions, a new relationship between human and automation is dawning. This relationship is moving from master-servant to teammates and necessitates a different approach to system design, human-machine information exchange and interface, as well as placing additional requirements on the machine.

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REFERENCES

Beller, J., Heesen, M., and Vollrath, M. (2013). Improving the driver-automation interaction. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 55(6), 1130–1140. doi:10.1177/0018720813482327. URL `http://dx.doi.org/10.1518/001872006779166334`.

Chen, J.Y.C., Procci, K., Boyce, M., Wright, J., Garcia, A., and Barnes, M. (2014). Situation awareness-based agent transparency. Technical Report ARL-TR-6905, U.S. Army Research Laboratory. URL `http://www.arl.army.mil/arlreports/2014/ARL-TR-6905.pdf`.

Choe, R., Puig-Navarro, J., Cichella, V., Xargay, E., and Novakimyan, N. (2016). Cooperative trajectory generation using pythagorean hodograph bézier curves. *Journal of Guidance, Control, and Dynamics*, 39(8), 1744–1763. doi:10.2514/1.G001531. URL `https://doi.org/10.2514/1.G001531`.

Cronk, T.M. (2012). The military's robot pack mule. *Armed with Science*. URL `http://science.dodlive.mil/2012/12/27/the-militarys-robot-pack-mule/`.

Endsley, M.R. (1995). Toward a theory of situation awareness in dynamic systems. *Human Factors*, 37(1), 32–64. doi:10.1518/001872095779049543. URL `https://doi.org/10.1518/001872095779049543`.

Ensor, J. (2014). Us military try out futuristic robot 'pack mule'. *The Telegraph*. URL `https://www.telegraph.co.uk/news/worldnews/northamerica/usa/10967617/US-military-try-out-futuristic-robotic-pack-mule.html`.

Fairley, P. (2017). The self-driving car's bicycle problem. *IEEE Spectrum*. URL `https://spectrum.ieee.org/cars-that-think/transportation/self-driving/the-selfdriving-cars-bicycle-problem`.

Greenwood, E. (2017). Real time helicopter noise modeling for pilot community noise awareness. In *Noise-Con 2017*.

Greenwood, E., Rau, R., May, B., and Hobbs, C. (2015). A maneuvering flight noise model for helicopter mission planning. In *Annual Forum Proceedings – AHS International*, volume 1. SKU # 71-2015-024.

Gregory, I.M., Leonard, C., Scotti, S.J., and Washburn, A. (2016). Self-aware vehicles: Mission and performance adaptation to system health. In *16th AIAA Aviation Technology, Integration, and Operations Conference*. AIAA. doi:10.2514/6.2016-3165. URL `https://doi.org/10.2514/6.2016-3165`. Paper no. AIAA 2016-3165.

Gregory, I.M., Rizzi, S., Neogi, N., and Siochi, E. (2018). Self-aware vehicles for urban air mobility: Challenges and opportunities. In *AIAA Guidance, Navigation, and Control Conference*. Collaborative Sensing, Learning, and Control in Human-Machine Systems workshop presentation.

Gregory, I.M. and Trujillo, A.C. (2016). Self-aware vehicles for effective human-machine teaming. In *2016 American Control Conference*. URL `http://web.me.iastate.edu/soumiks/workshops/acchms2016/resources/ACCHMS2016_Gregory.pdf`. Collaborative Sensing, Learning, and Control in Human-Machine Systems workshop presentation.

Helicopter Association International Fly Neighborly Committee (2007). *Fly Neighborly Guide*. Helicopter Association International, 3rd edition. URL https://www.rotor.org/portals/1/Fly%202009.pdf.

Kirlik, A., Ackerman, K., Seefeldt, B., Xargay, E., Talleur, K.R..D., Carbonari, R., Sha, L., and Hovakimyan, N. (2017). *Advances in Aviation Psychology, Volume 2: Using Scientific Methods to Address Practical Human Factors Needs*, volume 2, chapter 6: Visualizing Automation in Aviation Interfaces, 45. Milton, Taylor and Francis.

Marinho, T., Lakshamanan, A., Cichella, V., Widdowson, C., Cui, H., Jones, R.M., Sebastian, B., and Goudeseune, C. (2016). VR study of human-multicopter interaction in a residential setting. In *2016 IEEE Virtual Reality (VR)*, 331–331. URL http://ieeevr.org/2016/program/videos/.

McGuirl, J.M. and Sarter, N.B. (2006). Supporting trust calibration and the effective use of decision aids by presenting dynamic system confidence information. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 48(4), 656–666. doi:10.1518/001872006779166334. URL http://dx.doi.org/10.1518/001872006779166334.

Puig, J., Xargay, E., Choe, R., and Hovakimyan, N. (2015). Time-critical coordination of multiple UAVs with absolute temporal constraints. In *AIAA Guidance, Navigation, and Control Conference*. AIAA. doi:10.2514/6.2015-0595. URL https://doi.org/10.2514/6.2015-0595. Paper no. AIAA 2015-0595.

Richtel, M. and Dougherty, C. (2015). Google's driverless cars run into problem: Cars with drivers. *The New York Times*. URL https://www.nytimes.com/2015/09/02/technology/personaltech/google-says-its-not-the-driverless-cars-fault-its-other-drivers.html.

Sarter, N. and Woods, D. (1992). Pilot interaction with cockpit automation: Operational experiences with the flight management system. *International Journal of Aviation Psychology*, 2(4), 303–321. doi:10.1207/s15327108ijap0204_5.

Sarter, N.B. and Woods, D.D. (1995). "From tool to agent": The evolution of (cockpit) automation and its impact on human-machine coordination. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 39(1), 79–83. doi:10.1177/154193129503900119. URL https://doi.org/10.1177/154193129503900119.

Sarter, N.B., Woods, D.D., and Billings, C.E. (1997). *Handbook of Human Factors & Ergonomics*, chapter Automation Surprises, 25. Wiley, 2nd edition.

Trujillo, A.C. (2018). Operator trust function for predicted drone arrival. In J. Chen (ed.), *Advances in Human Factors in Robots and Unmanned Systems: Proceedings of the AHFE 2018 International Conference on Human Factors in Robots and Unmanned Systems, July 21-25, 2018, Orlando, Florida, USA*. Springer Nature. To be published.

Verberne, F.M.F., Ham, J., and Midden, C.J.H. (2012). Trust in smart systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 54(5), 799–899. doi:10.1177/0018720812443825. URL http://dx.doi.org/10.1177/0018720812443825.

Vicente, K.J. (1996). Improving dynamic decision making in complex systems through ecological interface design: A research overview. *System Dynamics Review*, 12(4), 251 – 279. doi:10.1002/(SICI)1099-1727(199624)12:4¡251::AID-SDR108¿3.0.CO;2-S. URL http://dx.doi.org/10.1002/(SICI)1099-1727(199624)12:4<251::AID-SDR108>3.0.CO;2-S.

Vicente, K.J., Christoffersen, K., and Pereklita, A. (1995). Supporting operator problem solving through ecological interface design. *IEEE Transactions on Systems, Man, and Cybernetics*, 25(4), 529–545. doi:10.1109/21.370186. URL http://ieeexplore.ieee.org/document/370186/.

Vicente, K.J. and Rasmussen, J. (1992). Ecological interface design: Theoretical foundations. *IEEE Transactions on Systems, Man, and Cybernetics*, 22(4), 589–606. doi:10.1109/21.156574. URL http://ieeexplore.ieee.org/document/156574/.

Widdowson, C., Yoon, H.J., Cichella, V., Wang, R.F., and Hovakimyan, N. (2018). VR environment for the study of collocated interaction between small UAVs and humans. In J. Chen (ed.), *Advances in Human Factors in Robots and Unmanned Systems*, 348–355. Springer International Publishing, Cham. doi:10.1007/978-3-319-60384-1_33.

Wilson, M. (2012). How lousy cockpit design crashed and airbus, killing 228 people. *Co.Design*. URL https://www.fastcodesign.com/1669720/how-lousy-cockpit-design-crashed-an-airbus-killing-228-people.