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An Analysis of Video Games Using the Dimensions of Human-Agent Interaction

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Abstract
Designers of human-agent interaction techniques may benefit from an analysis of existing video games that include aspects of human-agent teaming. Many popular multi-player video games have been designed to integrate multiple human and computer agents in pursuit of a common objective and can serve as a testbed to explore novel interaction methods in human-agent teams. A guiding framework of human-agent interaction was created to bridge best practices between video game and real-world domains. The framework was used to analyze games on five main dimensions: 1) Levels of Automation, 2) Levels of Interaction, 3) Control Mode, 4) Teaming, and 5) Interaction Timing. Two video games, Final Fantasy XIV and Mass Effect, were assessed to identify human-agent interaction paradigms, and ramifications for real-world applications for human-agent teaming. This research draws on interaction design principles, human-agent interaction theory, and existing video games to offer human-agent team designers potential examples of successful interaction paradigms.

Disciplines
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Comments
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An Analysis of Video Games Using the Dimensions of Human-Agent Interaction

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Designers of human-agent interaction techniques may benefit from an analysis of existing video games that include aspects of human-agent teaming. Many popular multi-player video games have been designed to integrate multiple human and computer agents in pursuit of a common objective and can serve as a testbed to explore novel interaction methods in human-agent teams. A guiding framework of human-agent interaction was created to bridge best practices between video game and real-world domains. The framework was used to analyze games on five main dimensions: 1) Levels of Automation, 2) Levels of Interaction, 3) Control Mode, 4) Teaming, and 5) Interaction Timing. Two video games, Final Fantasy XIV and Mass Effect, were assessed to identify human-agent interaction paradigms, and ramifications for real-world applications for human-agent teaming. This research draws on interaction design principles, human-agent interaction theory, and existing video games to offer human-agent team designers potential examples of successful interaction paradigms.

INTRODUCTION

The advance of automated systems has stimulated a recent increased demand for research on the dynamics of humans working with agents and robots (Breazeal, 2017). In this paper, the term "agent" is used to include disembodied software agents as well as robots. Though the discipline is not new, multiple descriptors abound, typically comprised of the term "human-agent" or "human-robot" with a term such as "interaction," "team," "teamwork," "collaboration," or "group," with perhaps "social" added (e.g., "social robot" and "social agent"). Whether stakeholders of human-agent team (HAT) design come from industry (e.g., Industry 4.0), the military (Chen & Barnes, 2014), or the medical field (Bickmore, Pfeifer, & Jack, 2009), they seek theories, research results, and best practices around trust (Bindewald, Rusnock, & Miller, 2018), etiquette (Parasuraman & Miller, 2004; Yang & Dorneich, 2016), communication (William Evans et al., 2017), team member roles (Goodman, Miller, Rusnock, & Bindewald, 2016), and personalization (Gordon et al., 2016), to name a few characteristics of the human-agent relationships.

More specifically, when designing human-agent or human-robot collaboration, questions such as the following must be answered: how will the tasks be shared between humans and agent team members, how will the human interact with agents, and who will be in charge during the activity. This paper suggests that some guidance in answering these questions can be gained from examining the interaction designs within existing video games. By their nature, successful games that include elements of human-agent teaming have been played extensively, and the design refined for better gameplay. Thus, games provide a testbed where different human-autonomy interaction designs have been tested. The question arises, can games inform designers of best practices for human-agent interaction (HAI) and teaming from the game domain into real-world applications.

Gamification is a process applied to many domains, including finance, health, and education, and specifically refers to the use of video game elements, including interface design and persuasive technology, to engage users in otherwise non-game activities (Deterding, Sicart, Nacke, O'Hara, & Dixon, 2011). Additionally, the gaming industry has been active in testing user interaction techniques (McMahan et al., 2010). This experimentation with cutting-edge interaction design is possible because video games are not built to support external tasks, there is relatively low risk for poor performance, and the users are motivated to engage. This confluence of features allows video games the freedom to explore novel interaction methods that would otherwise not be feasible to implement with real people and at scale. A logical step is the application of existing HAI techniques in games like Mass Effect and Final Fantasy XIV to real-world HAI, such as the piloting of drones.

In this paper, we have developed a generalized framework that categorizes the fundamental dimensions of HAI of real-world and game applications (Table 1). This paper introduces the first step of creating the framework and next steps for full validation are provided in the future work section.

DIMENSIONS OF HUMAN-AGENT INTERACTION

For each of the five dimensions in the framework of Table 1, several levels were defined by reviewing the literature in that area. In some cases, the levels within a dimension were simplified to be somewhat coarse-grained, since we hoped to apply the framework across many different domains and types of games. The simplification process was performed for each dimension as follows: (1) the literature review was performed to list different levels from various established frameworks for each dimension, (2) the similarities between different levels of established frameworks of each dimension are identified, and finally (3) these similarities for each dimensions' levels were identified with a level name that can describe what the level is. For instance, the vocabulary of different levels of automation from various frameworks (e.g. (Endsley, 1987; Endsley & Kaber, 1999; Parasuraman, Sheridan, & Wickens, 2000; Riley, 1989; Sheridan & Verplank, 1978)) have been examined and the levels were reduced to four levels to keep the descriptions fairly general. The goal was to build a vocabulary relevant across both games and real-world domains. In order to analyze the HAT dynamics within games, five main dimensions are defined: 1) Levels of Automation (LoA), 2) Levels of Interaction, 3) Control Mode, 4) Teaming, and 5) Interaction Timing. These variables for human-agent teaming were identified by reviewing the literature on human-agent/automation/robot interaction, reviewing the interaction styles in relevant games, and characterizing the relationship between human and agent in a team. Levels of each variable have been identified by comparing and categorizing the levels used for each variable dimension in the previous studies. Before detailing these dimensions, it is important to understand the concept of function allocation. Some of the functions performed in a work system will be allocated to the human, and some to the agent.

Table 1: Categorization of dimensions for HAI

	Scales	Description
Levels of Automation	*No automation*	Human performs everything.
	Suggestive automation	Agent gives suggestions to human (opt-in).
	Authorized automation	Agent performs tasks without human input. If needed, agent asks for human veto (opt-out).
	Full automation	Agent performs everything without human participation.
Level of Interaction	*No interaction*	No interaction between human and agent, but agent is present.
	Output level	Human must approve or disapprove the agent's action or selection.
	Dialog level	Agent and human perform tasks by communicating and sharing responsibilities.
Control Mode	*Supervisory*	Human assigns tasks to agent.
	Participation	Human assigns tasks to agent while performing with agent.
	Human-Initiated Adaptive	Human adjusts the control mode based on the situation.
	Agent-Initiated Adaptive	Agent adapts control mode based on the situation.
Teaming	*Multi-agent & Single-human*	Team configuration with multi-agent and a human.
	Single-agent & Single-human	Team configuration with single-agent and a human.
	Single-agent & Multi-human	Team configuration with single-agent and multi-human.
	Multi-agent & Multi-human	Team configuration with multi-agent and multi-human.
Interaction Timing	*Asynchronous*	Actions are pre-decided and carried out at a later time.
	Rewind	Actions can be revisited for reflection or before finalizing.
	Pause	Actions are decided while time stops.
	Real-time	Actions are decided and carried out simultaneously.

Function Allocation

Function allocation within HAI determines which entity performs what task, or function (Feigh & Pritchett, 2014; Hoc, 2000). Improving automation technology enables agents to perform more tasks alone, and humans are sometimes viewed more as the primary backup rather than a collaborator (Hoc, 2000). Also, human roles are often relegated by default to the tasks that are too difficult or expensive to automate. This inequity can lead to destructive competitive interactions, rather than productive ones, e.g., *Race Against the Machine* (Brynjolfsson & McAfee, 2011). Since games are inherently designed to be engaging for humans, they may offer role models of HAI that is complementary rather than inequitable.

Dimension 1: Level of Automation

In an autonomous system, LoA refers to the degree of autonomy (Vagia, Transeth, & Fjerdingen, 2016) and function allocation that the system has in a HAI. Various frameworks for LoA have been proposed (e.g. Endsley, 1987; Proud, Hart, & Mrozinski, 2003; Sheridan & Verplank, 1978); this paper described the levels for this dimension by comparing and categorizing the levels used in previous frameworks.

Sheridan & Verplank (1978) introduced a 10-point LoA scale with Level 1 as no automation and Level 10 as full automation. Since then, at least 12 proposed frameworks for LoA have been published (see Vagia et al., 2016, for a comparison). Generally, these frameworks vary in terms of their focus. The level could be based on who makes decisions and selects actions (Endsley & Kaber, 1999; Parasuraman et al., 2000), or could focus on a specific domain. For example, the SAE International standards for autonomous vehicles focus on the level of automation needed to support varying levels of human control of the vehicle (SAE International, 2014).

Drawing on previous frameworks to apply LoA principles to video games, four levels were identified (see Table 1): (1) *no automation* – there is no or almost no automation involved into the process that the human performs; (2) *suggestive automation* – the automation system provides decision alternatives and leaves the selection and execution to human; (3) *authorized automation* – the automation system generates alternatives, selects one, and executes actions, allowing time for human veto; and (4) *full automation* – the automation system acts without allowing human veto.

Dimension 2: Level of Interaction

While LoA defines the level of authority and behavior an agent has, the level of interaction describes how it interacts with the human(s). There is a complex tradeoff between the amount of automation and complexity of interaction; very high or very low automation can make interaction simpler.

For this research, three interaction levels were identified as (1) *no interaction* – there is no interaction between human and agent due to either low or high LoA, (2) *output* – the agent offers suggestions for human approval, and (3) *dialog* – agent and human maintain continuous communication to achieve their goals. These levels should be considered alongside LoA to determine the agent’s behavior in a team.

Dimension 3: Control Mode

Control Mode refers how the team members are organized and assigned roles. Scholtz (Scholtz, 2003) defines three major roles for human-robot team members as supervisor, operator and peer. Related to this dimension is the concept of responsibility, which may or may not align with supervisory authority. E.g., a human might be held responsible for flight safety while not being in authority over a co-pilot agent.

In this research, four levels of control mode were identified as (1) *supervisory*, (2) *participatory*, (3) *human-initiated adaptive*, and (4) *agent-initiated adaptive*. At the *supervisory level of control*, the human assigns functions and tasks to agents as needed. In *participatory control*, the human both assigns tasks to the agents and performs tasks alongside them. In *human-initiated adaptive control*, the human adjusts his or her control mode in case of situational necessity, while in *agent-initiated adaptive control*, the agent offers different modes of control based on the needs of the human. For an example of human-initiated adaptive control, the docking systems in International Space Station require a human team member to activate the automated docking mechanism when a ship approaches the station (Otero, Chen, Miller, & Hilstad, 2002). In contrast, an example of agent-initiated adaptive control might appear in a self-driving car that requests that a human take control under specific circumstances, e.g., an automated system alerting in an Uber car to tell the driver to take control (Gould, Han, & Muoio, 2016).

Dimension 4: Teaming

Because HATs can vary in their structure, e.g., a human controlling multiple agents, or a team of humans, each with his or her own agent, it is useful to categorize the team structure. These structures give insight into the complexity of team cognition for a given team, the ability of the team members to form shared mental models of each other's roles and activities (Fiore, 2012).

Teaming dimension has four levels: (1) *single agent, single human*, (2) *multi-agent, single human*, (3) *single agent, multi-human*, and (4) *multi-agent, multi-human*. Teaming dimension and control mode should be considered together. A multi-agent single-human team in which the human holds supervisory control might be a team of drones piloted by a single person, while the same teaming level with a human in a participatory role would be a very different team (e.g., a factory with one human working alongside multiple autonomous manufacturing robots).

Dimension 5: Interaction Timing

With HATs, it is useful to distinguish between teams in which agents are given instructions in real-time as the work unfolds (*real-time* timing) and teams in which agents are given direction and then left alone until they return with work completed (*asynchronous* timing). Examples include pre-programmed drones and turn-based role-playing games in which players specify actions for the agents before they execute the actions. In games, there are additional levels of timing control. In some games, players have the ability to pause time while they assign complicated agent actions (*pause* timing) or even try out an action tentatively, view its results, and then rewind time to explore another option (*rewind* timing). While these latter levels of interaction timing are impossible in real-world interactions HATs, they could be used for training people to work with automated systems.

ANALYSIS & CASE STUDIES

The dimensions described above were used to analyze two examples of video games (Final Fantasy XIV and Mass Effect) to evaluate the framework of this work. These games were chosen from an initial pool of 25 games. Mass Effect is a single-player role-playing game (RPG), while Final Fantasy XIV is a massively-multiplayer online role-playing game (MMORPG). Final Fantasy includes a diverse range of the dimensions discussed in Table 1, above, which made it an ideal candidate for dissection. Real world examples were also discussed for each dimension.

Final Fantasy XIV

Final Fantasy XIV (FFXIV*)* is a MMORPG developed and published by Square Enix (2010). The player has access to many different classes of characters that each have their own skill sets and interaction styles. FFXIV provides multiple examples of LoA. Because players must satisfy different game mechanics depending on the fight that they are in, the game also offers multiple examples within the framework.

Levels of Automation. In FFXIV, three levels of automation are present: *no automation*, *authorized automation*, and *full automation*. For the most part, players do not interact with or control autonomous agents unless they choose a specific character class, yet the control of each player's character is an example of *no automation* in the same sense that a teleoperated robot is an example of *no automation*. The control of the player character is not classified as automation because the player directly controls the movement and interactions of the virtual character.

Summoner is one of the specific classes that focuses on dealing damage to enemies with the help of autonomous "pets." The Summoner class is unique in FFXIV, because anyone playing it is expected to interact with the autonomous pet to optimize the amount of damage the Summoner/pet team deals to enemies. So, while the pet is capable of being fully autonomous, most players use the partial automation mode, which is most similar to *authorized automation*, as the pet will attack its own until it is told to stop or to use a special skill.

The third form of automation in FFXIV appears during single-person combat, which is required periodically for story reasons. In these fights, the player is joined by non-player characters (NPCs) who operate autonomously alongside the player. Because the NPCs do not require configuration during the game, they are an example of *full automation*.

Levels of interaction. In FFXIV, there are two potential levels of interaction with autonomous agents: *no interaction* and *output level* interaction. To continue the example of the Summoner and her pet, when the pet is summoned, it starts in an authorized automation state. In this state, there is no need for the interaction between Summoner and her pet (*no interaction*). This level of interaction is true for any player who is on a team, or "party," with a Summoner as a different combat class. When playing as a Summoner after switching the pet's state to another partially autonomous state called "obey," the interaction becomes much closer to the *output level* of interaction, in which the player has the ability to choose special attacks for the pet. The player is also always able to tell the pet to move to a specific area, to stop attacking, and to return to the player's character.

Control modes. The main control mode exemplified by the Summoner/pet interaction is *human initiated adaptive control*. As mentioned, the pet will attack its own without the control of the player. However, to get maximum damage output from the pet, the player must take control sometimes, to either get the pet into range to hit a specific enemy, to get the pet out of an area-of-effect attack, or to control when the pet uses specific skills.

Teaming. Final Fantasy XIV offers examples of teaming which fall into all of the four categories in the framework. While the player fights enemies on their own, the player has the option of using an autonomous agent, called a "Chocobo," which helps defeat enemies without the help of other players. If the player is using only the Chocobo, the team configuration is *single-agent single-human*. However, since a Summoner can use a pet and a Chocobo, the team configuration can also be *multi-agent single-human* in this context. In dungeons, areas in which a group of players with specific roles team up to fight a multitude of enemies, there are often multiple people per team who play as a Summoner, or another character class that works with an autonomous agent. In a team with more than one of those classes present, the team configuration is *multi-agent multi-human*. On the other hand, a team with only one of those classes present is of the *single-agent multi-human* team configuration.

Interaction timing. Final Fantasy XIV offers real-time interactions due to being a multiplayer game.

Mass Effect

Mass Effect is a single player, third-person shooter, role-playing game developed by Bioware and published by Electronic Arts (https://www.masseffect.com). The player is able to choose two teammates who act as NPC agents for the player to direct.

Level of automation. Mass Effect falls under the level of *authorized automation*. In combat scenarios, agent teammates act on their own, *authorized automation,* unless given input by the player. This input includes where agents should position themselves, what weapons to fire, and what targets to choose. Without input, agents make these decisions on their own. Outside of combat, agents can be sent by the player character to complete missions without the player's involvement. These activities effectively then act as *authorized automation* where the agents only act autonomously once sent by the player character.

Level of interaction. The game primarily has the player character to operate within the *output level* of interaction. During gameplay, players can call a menu of actions available to themselves and their agent teammates. These actions can be selected to both stop a current action and command a new action.

Control modes. Mass Effect uses both the *supervisory* and *participation* levels of control. In combat scenarios, the player is an active participant with his or her own character that is fighting alongside the two agents. These situations require the player to directly control their own actions and give direct commands to the two agent teammates. Outside of combat, in the scenarios that have agents sent to complete missions without player involvement, *supervisory* control is utilized. This requires that the player assign tasks to the agents to carry out without participating directly.

Teaming. Mass Effect is an example of *multi-agent single-human* teaming. One player directs two agents for the majority of the game.

Interaction timing. In single player scenarios, Mass Effect employs a time *pausing* system in which the player can pause the game state to evaluate the scenario and assign tasks to the agent teammates, such as attacking, moving, and performing actions. The player then decides when to resume the game state and the game continues to move forward. This system is particularly useful in complicated combat scenarios which changes the dynamic of the game from active participant to supervisory tactics, back to active participant upon resume.

From Games to Real-World Applications

After discussing the two video games this section describes analogous real-world HATs that might benefit from features of these games.

Levels of automation. The LoA described in the games is similar to automation levels for different types of drones in the real world. For instance, teleoperated drones require that their human operators carry out most functions, as is true for most player's characters in FFXIV. Similar to *authorized automation* within Mass Effect agents, Amazon Air Prime, utilizes autonomous drones that operate without human intervention to fly to a specific address (Amazon, 2018).

Levels of interaction. The *no interaction* and *output* levels of interaction again map to those found in drone operation. At the *no interaction* level, an Amazon Air Prime drone does not require a human to deliver a package, while with *output interaction*, a combat drone needs a human to confirm fire based on the images it outputs.

Control mode. In *human initiated adaptive control*, there is a clear tie to the docking system of the International Space Station as explained above, which requires human authorization. In *participation* scenarios, real-world farmers may take direct control over their combine harvester with GPS-based steering and automated settings adjustments and then relinquish control back to the system when they are satisfied that the system is working as intended.

Teaming. Traditionally the Predator combat drone has required two simultaneous human operators (Draper & Ruff, 2000), thus being a *single-agent multi-human* team. For modern drones, such as tree-planting drones (William Evans et al., 2017), the team configuration is often *multi-agent/single-human*, as a single operator controls multiple drones that plant trees in sparsely vegetated areas. A *single-agent single-human* team is best exemplified by semi-autonomous cars, while a *multi-agent multi-human* team is exemplified by BMW car manufacturing plant, in which humans work alongside robots to assemble cars (Kochan, 2006).

Interaction timing. A current real-world application for this type of time manipulation system can be found in training and after action review (AAR) scenarios within simulations for military, aviation, driving, agriculture, and other domains. Pausing the system state during flight simulator training allows for time-independent evaluation and discussion while in context. Similarly, after sporting events, teams review footage of performance for training purposes, and this approach can be built into future HAI training simulators.

DISCUSSION & FUTURE WORK

This research identified a variety of games that can serve as HAI examples, organized by five dimensions that can be used to characterize a HAT in its design process: level of automation, level of interaction, control modes, teaming, and interaction timing.

This research can help designers of systems for HATs address challenges such as how to communicate, how to negotiate function allocation, etc. HAI within video games offers an opportunity to observe and evaluate existing interaction models that carry many of the same requirements and constraints real-world applications have. By observing these interaction methods as they already exist and evaluating them for potential use in future real-world scenarios, research and development can be accelerated based on existing work.

In future work, we plan to further validate the framework. We will (1) perform a qualitative review on the implementation of the framework and (2) analyze not only the interaction design of the various HATs within video games but also the more detailed affordances for control and agent state that are used. How do games allow players to select agents and direct them? Which controls are most effective? Secondly, how do games give the human awareness of their agents' state, both within a scenario (e.g., "currently fighting a dragon and winning") and internal to the agent (e.g., "battery low; 4 minutes time remaining"). Further, if possible, these findings would be converted to recommendations for interaction affordances and human-agent etiquette guidelines that most effectively promote HATs. If these recommendations are created at the right level of abstraction, they will continue to apply as agents become smarter.

REFERENCES

Amazon. (2018). Prime Air. Retrieved October 2, 2018, from https://www.amazon.com/p/feature/6grqshfrw4gz7tv

Bickmore, T. W., Pfeifer, L. M., & Jack, B. W. (2009). Taking the time to care: empowering low health literacy hospital patients with virtual nurse agents. *Proceedings of the 27th International Conference on Human Factors in Computing Systems*, 1265–1274.

Bindewald, J. M., Rusnock, C. F., & Miller, M. E. (2018). Measuring human trust behavior in human-machine teams. In *Advances in Intelligent Systems and Computing* (Vol. 591, pp. 47–58).

Breazeal, C. (2017). Social Robots: From Research to Commercialization. In *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction* (p. 1).

Brynjolfsson, E., & McAfee, A. (2011). Race against the machine. Lexington, MA: Digital Frontier.

Chen, J. Y. C., & Barnes, M. J. (2014). Human–Agent Teaming for Multirobot Control: A Review of Human Factors Issues. *IEEE Transactions on Human-Machine Systems*, *44*(1), 13–29.

Deterding, S., Sicart, M., Nacke, L., O'Hara, K., & Dixon, D. (2011). Gamification. using game-design elements in non-gaming contexts. In *Proceedings of CHI EA'11* (p. 2425).

Draper, M., & Ruff, H. (2000). Multi-sensory displays and visualization techniques supporting the control of unmanned air vehicles. *IEEE International Conference on Robotics and Automation*.

Endsley, M. R. (1987). The Application of Human Factors to the Development of Expert Systems for Advanced Cockpits. *Proceedings of the HFES Annual Meeting*, *31*(12), 1388–1392.

Endsley, M. R., & Kaber, D. B. (1999). Level of automation effects on performance, situation awareness and workload in a dynamic control task. *Ergonomics*, *42*(3), 462–492.

Feigh, K. M., & Pritchett, A. R. (2014). Requirements for Effective Function Allocation A Critical Review. *Journal of Cognitive Engineering and Decision Making*, *8*(1), 23–32.

Fiore, P. B. M. and S. M. (2012). Team Cognition: Coordination across Individuals and Machines. *The Oxford Handbook of Cognitive Engineering*

Goodman, T., Miller, M. E., Rusnock, C. F., & Bindewald, J. M. (2016). Timing Within Human-Agent Interaction and its Effects on Team Performance and Human Behavior. In *2016 IEEE CogSIMA* (pp. 35–41).

Gordon, G., Spaulding, S., Westlund, J. K., Lee, J. J., Plummer, L., Martinez, M., … Breazeal, C. (2016). Affective personalization of a social robot tutor for children's second language skills. *Proceedings of AAAI 2016*, 3951–3957.

Gould, S., Han, Y., & Muoio, D. (2016). Here's the tech that lets Uber's self-driving cars see the world. *Business Insider*. Retrieved from: http://www.businessinsider.com/how-ubers-driverless-cars-work-2016-9

Hoc, J. M. (2000). From human-machine interaction to human-machine cooperation. *Ergonomics*, *43*(7), 833–843.

Kochan, A. (2006). BMW innovates at new Leipzig assembly plant. *Assembly Automation*, *26*(2), 111–114.

McMahan, R. P., Alon, A. J. D., Lazem, S., Beaton, R. J., Machaj, D., Schaefer, M., … Bowman, D. A. (2010). Evaluating natural interaction techniques in video games. In *2010 IEEE Symposium on 3DUI*.

Otero, A. S., Chen, A., Miller, D. W., & Hilstad, M. (2002). SPHERES: Development of an ISS Laboratory for formation flight and docking research. In *IEEE Aerospace Conference Proceedings* (Vol. 1, pp. 59–73).

Parasuraman, R., & Miller, C. a. (2004). Trust and etiquette in high-criticality automated systems. *Communications of the ACM*, *47*(4), 51.

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics. Part A, Systems and Humans*, *30*(3), 286–297.

Proud, R. W., Hart, J. J., & Mrozinski, R. B. (2003). Methods for Determining the Level of Autonomy to Design into a Human Spaceflight Vehicle: A Function Specific Approach. In *PerMIS '03*.

Riley, V. (1989). A General Model of Mixed-Initiative Human-Machine Systems. *Proceedings of the Human Factors Society Annual Meeting*, *33*(2), 124–128. http://doi.org/10.1177/154193128903300227

SAE International. (2014). *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles*. *SAE International* (Vol. J3016). Retrieved from http://standards.sae.org/j3016_201609/

Scholtz, J. (2003). Theory and evaluation of human robot interactions. *System Sciences, 2003. Proceedings of the 36th Annual Hawaii International Conference-IEEE.*

Sheridan, T. B., & Verplank, W. L. (1978). Human and Computer Control of Undersea Teleoperators. *ManMachine Systems Lab Department of Mechanical Engineering MIT Grant N0001477C0256*.

Square Enix Holdings Co. Ltd. (2010). Final Fantasy XIV [Computer Software]. Tokyo, Japan.

Vagia, M., Transeth, A. A., & Fjerdingen, S. A. (2016). A literature review on the levels of automation during the years. What are the different taxonomies that have been proposed? *Applied Ergonomics*.

William Evans, A., Marge, M., Stump, E., Warnell, G., Conroy, J., Summers-Stay, D., & Baran, D. (2017). The future of human robot teams in the army: Factors affecting a model of human-system dialogue towards greater team collaboration. In *Advances in Intelligent Systems and Computing*.

Yang, E., & Dorneich, M. C. (2016). Evaluation of etiquette strategies to adapt feedback in affect-aware tutoring. In *Proceedings of the Human Factors and Ergonomics Society* (pp. 393–397).