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Tomorrow's Human–Machine Design Tools: From Levels of Automation to Interdependencies

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The growth of sophistication in machine capabilities must go hand in hand with growth of sophistication in human–machine interaction capabilities. To continue advancement as we build today's intelligent machines, designers need formative tools for creating sociotechnical systems. In this article, we will briefly assess the appropriateness of "levels of automation" as a tool for designing human–machine systems. Additionally, we present coactive design and interdependence analysis as a viable alternative tool moving forward into more advanced and sophisticated human–machine systems.

Keywords: design methods, human–automation interaction, level of automation, cognitive engineering, collaboration, human–computer interaction, human–robot interaction, team design

INTRODUCTION

As any craftsman knows, having the right tool for the job makes all the difference. Sadly, adequate tools are lacking for the design of sociotechnical systems. The most widely known approach, which underpins many current efforts to build intelligent machines, is known as "levels of automation" (LOA). As the design of increasingly intelligent machines has brought new issues and options in human–machine interaction and teamwork to the fore, some researchers have increasingly expressed serious misgivings about the approach (Defense Science Board, 2012; Feigh & Pritchett, 2014; Johnson, Bradshaw, Feltovich, Hoffman, et al., 2011). The debate is not only about the theoretical adequacy of the constructs that underlie LOA but also about pragmatics: Does the LOA approach, when used as a tool, provide adequate guidance to designers of human–machine systems?

In this article, we will briefly assess the appropriateness of LOA as a tool for designing increasingly sophisticated human–machine systems. Additionally, we present interdependence analysis as a viable alternative tool moving forward into more advanced and sophisticated human–machine systems.

WHAT DO DESIGNERS NEED?

Design, as a verb, is about conceiving and creating. Designers of any system need to represent the components of the system and how they fit together. For sociotechnical systems, these components mean both the machine and the human. When designing something that performs a function, designers also need to represent the process or flow of activity necessary for that function. When creating something new, it is difficult if not impossible to anticipate all consequences of design choices, but that difficulty should not deter designers from pursuing tools that aid them in such predictions. For distributed, multiparty systems, which all sociotechnical systems are, a key capability to predicting performance is identifying and understanding causal relations within the work process. As such, human–machine design tools should be evaluated based on how well they represent both the human and machine, the work being performed, and the relationships between the human and machine throughout the work.

DOES LOA MEET THE DESIGNER'S NEEDS?

The original LOA concept was presented in Sheridan and Verplank's (1978) seminal work.

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TABLE 1: The 10 Levels of Automation Identified in Sheridan and Verplank (1978) as Presented in Parasuraman, Sheridan, and Wickens (2000)

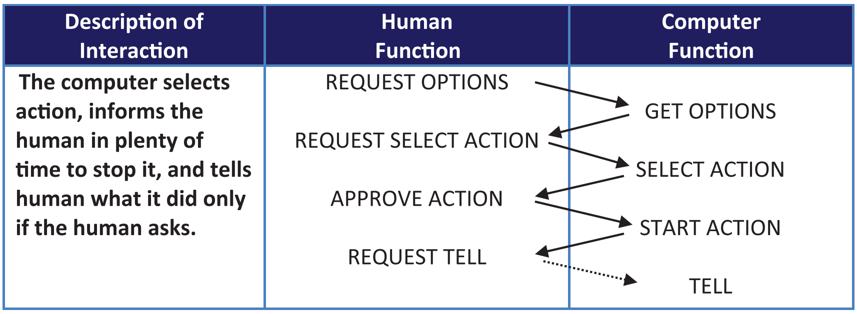
Level	Description
High	10. The computer decides everything and acts autonomously, ignoring the human.
	9. The computer informs the human only if it, the computer, decides to.
	8. The computer informs the human only if asked, or
	7. The computer executes automatically, then necessarily informs the human, and
	6. The computer allows the human a restricted time to veto before automatic execution, or
	5. The computer executes that suggestion if the human approves, or
	4. The computer suggests one alternative, or
	3. The computer narrows the selection down to a few, or
	2. The computer offers a complete set of decision/action alternatives, or
Low	1. The computer offers no assistance; the human must take all decisions and actions.

Parasuraman, Sheridan, and Wickens (2000) extended the original concept, arguing for a more multidimensional approach that considered the different information-processing phases (information acquisition, analysis, decision, and action). Arguing for a more complex model, they presented a simplified representation of the original work shown in Table 1, which ironically has been tremendously influential. When people think of LOA, they are most likely thinking of it as presented in Table 1. Most references to LOA follow its abbreviated format of an ordinal list of increasing automation, and as such it will be used as the baseline. (Table 1 is the most cited version of LOA, according to Google Scholar, with 2,211 citations—3 times the number of citations of the original work; accessed May 29, 2017, from https://scholar.google.com/scholar?cluster=8423741310274212639&hl=en&as_sdt=0,10). LOA approaches are based on function allocation, and the driving question is deciding what to automate (Parasuraman et al., 2000). So does LOA meet the designer's needs? Table 1 does represent the machine, but the human is included only with respect to the machine's actions. Similarly, the work being performed is representative of mainly the machine's work. The human activity is explicit only in Levels 1, 5, and 6 and is implicit in other levels. Each level focuses primarily on a momentary action or decision.

An interesting comparison can be made between the formulation of LOA in Table 1 and the original LOA work. The table in the original version was significantly bigger and more complex. Each level had not only a description but a column for the human function and a column for the computer function. Figure 1 is an adaptation of just one level, Level 6. The first column corresponds to an LOA in Table 1, but the description is labeled a "description of interaction" in the original work. The second column represents the human functions in the activity, and the third represents the functions the computer performs. This representation shows that two parties are involved in the activity more clearly than Table 1. Interestingly, arrows were used between the second and third columns in the original work, creating a small causal diagram. These arrows represent a work flow with dependencies connecting the functions. Each "level" in the original LOA models the full work process, not just an isolated moment within the work. This provides a richer context for understanding any given aspect of automation and supports a better understanding of the implication of design choices.

ARE THERE VIABLE ALTERNATIVES TO LOA?

Several alternatives to LOA have been proposed. For example, shared control (Sheridan, 1992) is an early approach that broke from the traditional function allocation approach of LOA. Mixed-initiative interaction (Allen, Guinn, & Horvitz, 1999) went further, proposing that joint



Description of Interaction	Human Function	Computer Function
The computer selects action, informs the human in plenty of time to stop it, and tells human what it did only if the human asks.	REQUEST OPTIONS REQUEST SELECT ACTION APPROVE ACTION REQUEST TELL	GET OPTIONS SELECT ACTION START ACTION TELL

Figure 1. Altered excerpt of Sheridan and Verplank's (1978) original Level 6 automation. The purpose of this example was to incorporate all the basic elements in a single level. It more clearly shows that two parties (computer and human) are involved in the activity, models the work flow, and expresses the casual relationships between the human and machine within the work.

activity is about interaction and negotiation. Collaborative control (Fong, 2001) introduced the idea that both parties may participate simultaneously in the same action, which also breaks with LOA. Klein, Woods, Bradshaw, Hoffman, and Feltovich (2004) proposed shifting focus from what should be automated to how to support teaming. They proposed 10 challenges for making automation a "team player" (Klein et al., 2004). Each of these alternatives to LOA contributes valuable insights into human–machine interaction and identifies new issues that have arisen since LOA was first conceived. The need to advance beyond the limitations of LOA is not a criticism of the work as a whole, merely a desire to continue advancement. This need was anticipated by the originators of the concept who predicted the "need for improved man-computer interaction will increase, not diminish" (Sheridan & Verplank, 1978, p. 1-10). All of these alternative approaches share a common goal of improving the guidance provided to designers building human–machine systems.

Our alternative to LOA is based on interdependence. Instead of considering how to allocate functions, the primary question is how to support interdependence. *Coactive Design* (Johnson, Bradshaw, Feltovich, Jonker, et al., 2011), is based on joint activity theory (Bradshaw, Feltovich, & Johnson, 2011; Klein et al., 2004; Klein, Feltovich, Bradshaw, & Woods, 2005) and is a generalization of Herbert Clark's (1996) work in linguistics. We coined the term *coactive* as a way of characterizing the activity. Besides implying more than one party is involved in the activity, the term *coactive* is meant to convey the type of involvement. It is meant to convey the reciprocal and mutually constraining nature of actions and effects that are conditioned by coordination. Consider an example of playing the same sheet of music as a solo versus a duet. Although the music is the same, the processes involved are very different (Clark, 1996). The implication is that the design of the process, in other words, the automated algorithm, must be different for joint activity. All "intermediate levels" of automation are joint activity, not cleanly separable functions to be allocated in isolation, thus the importance for designers to build algorithms not just to do work but to support interdependence.

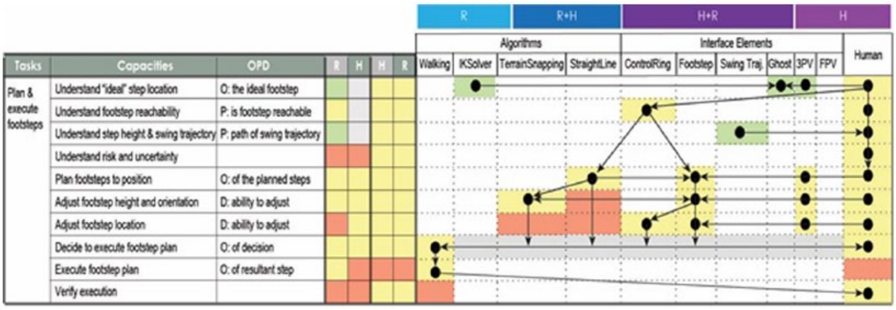
Shifting the designer's focus toward interdependence addresses a common misconception with LOA: that we are simply choosing what to automate as if it were a binary decision. However, "the simplistic description of 'automatic' and 'manual' control does not apply to many systems" (Gao & Lee, 2006). Coactive Design encourages thinking of the work as truly joint—coactive—and the binary options are just degenerate cases where the situation does not permit coordination. To effectively exploit automation's capabilities (versus merely increasing automation), we must coordinate the taskwork—and the interdependence it induces among players in a given situation—as a whole. We believe that increased effectiveness in human–machine systems hinges not merely on trying to make machines more independent through their automation but also on striving to make them better team players.

Coactive Design proposes three essential interdependence relations: observability, predictability, and directability (Johnson et al., 2014). *Observability* means making pertinent aspects of one's status, as well as one's knowledge of the team, task, and environment, observable to others. *Predictability* means that one's actions should be predictable enough that others can reasonably rely on them when considering their own actions. *Directability* means one's ability to influence the behavior of others and complementarily be influenced by others. There are certainly additional types of interdependence relationships, such as explainability and trust, but we view these three as foundational to the others. These relationships are also consistent with long-standing principles in human-centered design that suggest high-level performance is achieved by "ensuring that the human has the capability to monitor the system, that they receive adequate feedback on the state of the system, and that the automation functions in predictable ways" (Billings, 1997, p. 39). Billing's (1997) statement clearly speaks to the importance of observability and predictability. One of the common results found in LOA studies is that situation awareness significantly decreases with "higher" LOA (Kaber, Onal, & Endsley, 2000). Situation awareness, as defined by Endsley and Kiris (1995), is about perception (observability) and projection (predictability), so the failure of automation to support them explains these results.

The importance of these three interdependence relationships can be seen throughout automation literature with many references to observability (often referred to as transparency; Gao & Lee, 2006; Klein et al., 2004; Wiener, 1989), predictability (Kirlik, Miller, & Jagacinski, 1993; Klein et al., 2004; Rovira, McGarry, & Parasuraman, 2007; Wiener, 1989), and directability (Klein et al., 2004). Parasuraman et al. (2000) acknowledge the challenges of function allocation and state, "The performance of most tasks involves *interdependent* stages that overlap temporally in their processing operations" (p. 287, italics added by author for emphasis). Even when not called out directly, the interdependence relations can be found in results of some researchers who note how the elements of human–machine interaction "must be suitably matched" (Degani, Ames, & View, 2002). We propose that observability, predictability, and directability are core interdependence relationships that determine such suitability.

One advantage of coactive design is that its focus on core interdependence relationships can provide a formative tool for designers called interdependence analysis (IA; Johnson et al., 2014). Johnson et al., 2014, and Johnson et al., 2017, provide specific details on the interdependence analysis tool briefly discussed here. One of the limitations of LOA is that its predictive power derives from comparison of two different levels through empirical evaluation. Only through such evaluation does one understand how automation changes affect the nature of work in the human–machine system. It is a summative analysis. Summative assessment is important, but designers also need formative tools to guide the initial design. The need for formative tools is consistent with Kirlik et al. (1993), who emphasize "the importance of understanding why cognitive demands are present, prior to determining a strategy for aiding the operator in meeting these demands" (p. 950). Understanding and designing for interdependence can provide this type of guidance. It is important to understand not just what work the automation is doing but what needs to be observable, predictable, and directable in order to provide a designer this predictive power. IA provides insight into when situation awareness is adequately supported and when it is not. It can inform the designer of what is and is not needed, what is critical, and what is optional. Most importantly, it can indicate how changes in capabilities affect relationships. Unlike LOA, which really provides insight into what *could* be automated, interdependence analysis helps one understand what *should* be automated. (The original wording used by Parasuraman et al., 2000, is *should*, indicating a prescriptive model rather than a descriptive statement, but they clarify this wording by stating, "Our model does not therefore *prescribe* what should and should not be automated in a particular system"; p. 286).

Another key difference between LOA and coactive design is that we propose inverting the relationship between automation and interaction.



Tasks	Capacities	OPD	R	H	H	R
Plan & execute footsteps	Understand "ideal" step location	O: the ideal footstep	🟩	⬜	🟨	🟨
	Understand footstep reachability	P: is footstep reachable	🟨	⬜	🟨	🟨
	Understand step height & swing trajectory	P: path of swing trajectory	🟩	⬜	🟨	🟨
	Understand risk and uncertainty		🟥	🟥	🟨	🟨
	Plan footsteps to position	O: of the planned steps	🟨	🟨	🟨	🟨
	Adjust footstep height and orientation	D: ability to adjust	🟨	🟨	🟨	🟨
	Adjust footstep location	D: ability to adjust	🟥	🟨	🟨	🟨
	Decide to execute footstep plan	O: of decision	🟨	🟨	🟨	🟨
	Execute footstep plan	O: of resultant step	🟨	🟥	🟥	🟥
	Verify execution		🟥	🟥	🟨	🟨

Figure 2. Example interdependence analysis of planning footsteps for a humanoid robot.

LOA-based approaches choose what to automate, which dictates interaction. The interaction design is not addressed. As designers look to automate work, the work is decomposed and distributed, creating interdependencies. These interdependencies are what effects performance, and we propose they are what is predictive of human–machine system performance. As such, they are what designers must consider in order to better understand how people actually interact with automation and to be predictive of human–machine system outcomes. The fundamental principle of coactive design is that interdependence must shape automation (Johnson, Bradshaw, Feltovich, Jonker, et al., 2011). So what is the significance of the interdependence shaping automation instead of automation shaping interaction? When automation choices dictate interaction, one is limited to summative assessment. Designing for interdependence determines what is observable, predictable, and directable. This determination in turn shapes the interaction and the underlying automation, thereby permitting formative assessment due to the major role interaction plays in overall performance.

As a brief example, consider the task of planning footsteps for a humanoid robot. LOA might provide a set of LOAs, such as providing a set of alternative paths (Table 1, Level 3), providing a single option (Level 4), executing the suggested plan on approval (Level 5), and executing and automatically informing the human if asked (Level 8). What are the risks with each option? How does the interaction change? Can there be any other interaction with the system? As a design tool, LOA is silent on all of these key design questions.

Now consider Figure 2, which shows what an IA might look like for the same design problem. Considering our designer's needs stated earlier, IA models both the human (far right column) and the machine (both algorithms and interface element columns). IA also models the work. Similar to cognitive task analysis, the column under "Capacities" breaks down different aspects of the work involved in the task. Most importantly, IA models the potential interdependencies between the human and machine. Interdependencies are captured in the color-coded columns 4 through 8, which consider how each can support the other. For systems with designed components, these components can also be represented, as depicted by the right-hand columns, which capture the different work flow alternatives in a graph structure. This graph allows the IA table to model multiple control paradigms simultaneously. The observability, predictability, and directability requirements, in the "OPD" column, correlate to interface elements to meet human interaction requirements and drive algorithm design. IA also includes a color-coding scheme that broadly captures how well both the human and machine can perform in different roles. Pathways crossing red are risky due to lack of information. Yellow paths are less risky, but if they pass through both the human and machine, each can potentially mitigate the other's weaknesses. Each pathway is a potential alternative, and the observability, predictability, and directability requirements help one understand how interaction changes with each option.

SUMMARY

The growth of sophistication in machine capabilities must go hand in hand with growth of sophistication in human–machine interaction capabilities. To continue advancement as we build today's intelligent machines, designers need formative tools for creating *sociotechnical* systems. LOA-based approaches based on function allocation are not formative and do not effectively model the human or the work. As an alternative to LOA, we propose designing for interdependence—coactive design. IA provides a formative tool that explicitly models the machine, the human, and the work. We further propose that interdependence should shape automation design, instead of letting automation design dictate interaction. It is the interdependencies that are predictive of human–machine system outcomes, thus their growing importance as we develop tomorrow's advanced human–machine systems.

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