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Rania Afiouni
McGill University, rania.afiouni@mail.mcgill.ca

Alain Pinsonneault
McGill University, alain.pinsonneault@mcgill.ca

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Rania Afiouni
McGill University
1001 Sherbrooke St W, Montreal, QC
H3A 1G5, Canada
rania.afiouni@mail.mcgill.ca

Alain Pinsonneault
McGill University
1001 Sherbrooke St W, Montreal, QC
H3A 1G5, Canada
alain.pinsonneault@mcgill.ca

Abstract

Artificial Intelligence's (AI) potential to augment knowledge workers' jobs brings about significant transformation in their work, permeating their entire job beyond the automated tasks. Consequently, their established control perceptions can be disrupted. We therefore propose a model of worker adaptation to the AI work environment via personal control processes aimed at aligning the environment and the self. The Human-in-Control (HiC) model is a dialectical process of trust in AI's task execution ability and direct control over tasks that synthesizes in an expectation of delegation success leading to one of four control processes—expansive, opportunistic, investigative, preventive, and disengaging. The reached control state ranges from augmenting to reducing or, in extreme cases, slides down to uncontrollability. These states are transient, with feedback potentially prompting adaptive recalibration and state changes. Our study introduces personal control as an adaptive process in augmentation, expanding adaptation's scope and guiding human-centered empirical investigations of job-wide adaptation.

Keywords: personal control, artificial intelligence, delegation, Human-in-Control, adaptation

Introduction

With Artificial Intelligence (AI), technology is shifting from assisting knowledge workers to augmenting them (Krakowski et al. 2023). Augmentation entails a paradigmatic shift in the relationship between humans and machines (Lyytinen et al. 2021; Rahwan et al. 2019) where work is redistributed in a new division of labor allocating to each what they do best (von Krogh 2018). Perhaps most notably, AI has challenged a long-standing belief that automation concerned doing tasks while sparing thinking ones (Phan et al. 2017), exposing knowledge workers to significant task replacement as higher cognition tasks are delegated to the machine (Baird and Maruping 2021; Benbya et al. 2020). As these knowledge workers adapt to novel forms of human-AI collaboration and hybrid configurations, their work is transformed in unprecedented ways (Coombs et al. 2020; Rai et al. 2019; Shrestha et al. 2019; Zhou et al. 2021). This is especially important in the case of AI that first is based on deep learning algorithms where rules of machine behavior emerge from data rather than human specifications (LeCun et al. 2015), and second that does not substitute humans but rather augments them in an ecosystem for joint human-machine decision-making (Shrestha et al. 2019).

Studies that have investigated transformation through augmentation and how knowledge workers adapt to it have mostly done so with a focus on the joint decision-making process in light of AI's opacity. Algorithmic opacity or the blackbox effect is a notorious characteristic of AI technologies that presents an inherent obstacle to humans understanding the rationale of an AI decision or recommendation (Burrell 2016). In its simplest explanation, it refers to the intelligent system's unknowable relationship between its input and output (Tang et al. 2022). This limited ability to find a rationale for algorithmic decisions has led some workers to reject critical AI decisions for reasons such as divergence from their judgment (Lebovitz et al. 2022) or fear of unintended consequences, especially at high levels of expertise (Allen and Choudhury 2022). Workers who benefited the most from AI's recommendations were found to be the ones who, instead of blacboxing algorithmic advice, expended considerable effort to engage in interrogating its underlying reasoning, relating it to their own knowledge, and assessing its validity (Jussupow et al. 2021; Lebovitz et al. 2022), even when they agreed with it (Anthony 2021). This additional cognitive effort was particularly observed when the machine disconfirmed the decision maker's prior beliefs and expectations, leading potentially to a reduction in efficiency, especially under conditions of high pressure on the worker (Boyaci et al. 2023). In these situations of conflict, both the context and the medium of the interaction influence whether the decision is human or machine-dominated (Bader and Kaiser 2019). When facing such transformed decision-making, workers develop coping strategies to deal with the change (Beaudry and Pinsonneault 2005), leading to either disruption or empowerment to use the intelligent systems to their full potential for better performance Chen et al. (2022). Usage of intelligent systems was however found to be sometimes detrimental to performance, particularly for conscientious employees whose orderliness might be non-complementary with the machine's unknown and autonomous workings (Tang et al. 2022).

This difficulty in understanding the machine's workings is at the heart of recent studies in individuals' augmentation, which provide valuable insight into the relationship between AI and knowledge workers who use it. These studies therefore share an assumption of use and are micro-focused on the interface between the user and AI, which places the adaptation discussion in proximity to the automated tasks. However, while adaptation to changes induced by augmentation might be observed most directly and evidently in the execution and consequences of the automated tasks, its scope is much larger. Beyond these AI tasks, the symbiotic nature of augmentation has a transformative effect that also impacts the more complex often non-routine and irreplaceable tasks comprised in the same job (Autor 2015; Benbya et al. 2020; von Krogh 2018). The few studies that stepped away from the use assumption either concerned a full-automation decision scenario where the AI is substitutive and workers do not interact with it (Strich et al. 2021), or focused on workers' emotions and feelings as AI changes the meaning and morality of their work rather than on job transformation (Rauch and Ansari 2021).

Widening the scope of adaptation calls for a move away from a lens of use and toward a lens of delegation, which is more adapted to the agentic nature of AI and its capabilities (Baird and Maruping 2021; Fügener et al. 2022). Fundamentally, AI challenges a major premise of use whereby a human effectively applies a tool to accomplish a goal. Tool application fails to fully capture the richness and complexity of the relationship between a human worker and an agentic AI artifact that is capable of both behavior and cognition (Baird and Maruping 2021; Rahwan et al. 2019). Delegation acknowledges an important characteristic of AI, its autonomy. The delegated task is realized by the AI agent through exerting autonomy (Castelfranchi and Falcone 1998). Still, AI has "the capability … to act autonomously, but on behalf of humans, organizations, and institutions." (Agerfalk 2020, p. 5). Since machine action is on behalf of others, this type of autonomy entails neither consciousness nor responsibility (Agerfalk 2020). Therefore, the transfer of rights and responsibilities for the execution of the delegated task among the human and non-human agents (Baird and Maruping 2021) does not translate into a transfer of responsibility for its outcome. The opaque and autonomous AI has therefore introduced knowledge workers to the challenge of a machine that thinks, learns, develops intentions, and exhibits a dynamic behavior of its own (Agerfalk 2020; Lyytinen et al. 2021; Rahwan et al. 2019) which is not transparent and for which they are responsible (Coombs et al. 2020). This tension in delegation between autonomy and opacity on one hand and accountability on the other makes a control perspective particularly relevant to studying the adaptation of knowledge workers. As they work with a technology that shares the tasks not the responsibility and that lacks transparency, these workers adapt by seeking new ways of maintaining a sense of control.

We propose a personal control adaptation model, arguing that the AI-induced transformation of their work disrupts knowledge workers' sense of control and renders irrelevant old ways of maintaining control. A personal control disruption inevitably leads individual workers to strive to restore it (Leotti et al. 2010; Rothbaum et al. 1982). We differentiate between personal control as a sense of control at work and direct control over specific tasks. Indeed, adaptation anchored in a delegation perspective can lead to a sense of control through either keeping or relinquishing direct control. Adaptation in that sense is a process of restoring or gaining personal control, which places the emphasis on worker cognition and behavior throughout the whole job. Bringing control to the fore of the augmentation conversation places the human at its center, not just as a user interacting with the intelligent machine and dealing with opacity problems, but as a full-fledged job performer. Through our Human-in-Control (Hic) model, we answer calls for more research on workers' attitudes and behaviors when augmented by intelligent systems (Coombs et al. 2020; Zhou et al. 2021). The HiC model is a process through which individual workers follow different paths to reconstruct their sense of control at work. We aim to provide through it a theoretical basis for empirical research investigating job-encompassing rather than task-reactive adaptation. To our knowledge, this is the first study that introduces personal control as an adaptive process in augmentation contexts. We present a new perspective of adaptation to augmentation as a control phenomenon, making visible part of adaptation that is invisible through the narrow use lens.

In the following sections, we first explain background theories in delegation and personal control, highlighting how an emphasis on delegation allows a better appreciation of the control workings in augmentation. We conceive personal control as an alignment process of the self and environmental forces that starts with changing the environment and then, short of changing it, aligns the self with it (Rothbaum et al. 1982). We follow with the development of the HiC model from the link between trust in AI and direct task control to different control processes and the control states they lead to. Finally, we discuss future research avenues building on our model.

Background Theories

We follow Baird and Maruping's (2021) recommendation to consider delegation in augmentation studies. We describe the background theories of delegation and control and explain how delegation is essential for understanding adaptation to augmentation through control.

Delegation

Delegation can broadly be described as a process where one entity acts *on behalf* of another (Castelfranchi and Falcone 1998). Several studies have praised its benefits at multiple levels (Brynjolfsson and McAfee 2017). In particular, delegating task performance to an agent – delegatee – frees the delegating agent – delegator – and their resources for other work (Lyytinen et al. 2021).

The relevance of delegation to our control emphasis is corroborated by the many intricacies that differentiate delegation to a human versus non-human agent. A first difference is in accountability. While the delegator remains responsible for the delegated activities and liability cannot be transferred (Liu et al. 2001), this is often relaxed in human delegation as responsibility for failed outcomes can be passed on to a subordinate (Bushardt et al. 1991). Such practice is not possible in delegation to a machine (von Krogh 2018; Rahwan et al. 2019), although even the simplest applications such as email agents making a decision to discard a supervisor's message can have severe consequences for employees (Liu et al. 2001), hence the importance of both delegation and control. The second one is the type of intelligence. Currently available AI is referred to as weak AI having a narrow intelligence that exceeds by far human capabilities, only in performing a very specific task or type of tasks (Zhou et al. 2021). However, the algorithm's focus on specific tasks without contextual considerations can be highly problematic, making AI incapable of ethical judgment, symbolic reasoning, or social management (Brynjolfsson and McAfee 2017) and limited in its context awareness despite recent advancements (Randolph et al. 2022). Unlike machines, humans can quickly respond to unusual events and incorporate important contextual factors such as organizational politics. Third, unlike most cases of delegation to humans, delegation to an agentic AI artifact is highly open given the opacity of the technology. In an open delegation, the delegator has no knowledge of how the delegatee is performing the task (Castelfranchi and Falcone 1998), adding to the risk of delegation. Fourth, delegation to machines is unilateral in that an intelligent machine agent is assigned a task without having agreed to it. Agreement is indispensable for true collaboration and strong reliance on the other (Castelfranchi and Falcone 1998). Collaboration, which is often cited alongside augmentation, thus has its limits when it comes to machine agents compared to humans. A salient limit relates to communication throughout the delegation process. Since accountable for the task outcome, the delegator is likely to communicate with a human delegatee to either get updates, give directions, ask for justification, or rectify midway a poor performance (Di Nucci 2020). Such seemingly simple interactions can be challenging or sometimes impossible when applied to AI. These particularities of delegating to AI have implications on the augmented human's personal control and support the relevance of delegation for studying it.

Personal Control

Personal control is an innate psychological necessity for every human being. It is therefore safe to assume that the need for control is desirable and that people naturally try to increase their personal control (Leotti et al. 2010; Rothbaum et al. 1982). In an organizational setting, employees' perception of personal control is positively associated with job satisfaction, commitment, involvement, motivation, and performance, and negatively associated with stress and turnover (Baronas and Louis 1988). Conversely, a loss in the sense of control may result in withdrawal and sabotage with serious consequences for mental health and wellbeing (Rothbaum et al. 1982; Skinner 1995). Personal control is therefore not only desirable, but also essential.

While the need for control is basic and naturally motivated, the perception of personal control is influenced by external factors such as personal experience and learning (Leotti et al. 2010). Introducing any IS in an organization brings about changes to both, especially in the form of involuntary transition for users involving changes to their role, and therefore represents a threat to personal control. Changes are sometimes official, but most often entail an informal reorientation in the form of altered demands, resources, or priorities (Baronas and Louis 1988). Yet, personal control has been quite absent apart from few studies that attribute its loss to communication overload in the context of email use (Barley et al. 2011). With the advent of intelligent agentic artifacts, personal control gains in importance and we need to make available for IS researchers a model that attends to it.

In their seminal article in psychology, Rothbaum et al. (1982) conceptualized personal control as a two-process alignment of the self and the environment. The first process brings the environment into line with one's wishes, and the second refocuses the change efforts on the self to bring it into line with environmental forces. The two processes are not mutually exclusive, but rather intertwined and thought to always coexist. However, differences in emphasis are noted whereby when the former is salient, the process is termed primary control, and when the latter is salient, it is termed secondary control. A perception of control, especially secondary, can be reflected through any or all of four manifestations: predictive control (ability to predict outcomes and adjust expectations accordingly), illusory control (associating self with chance rather than skills), vicarious control (associating self with powerful others), or interpretive control (deriving meaning from otherwise uncontrollable situations).

Of critical importance to our model, this process conceptualization of control means that control perception changes over time and, unlike other control concepts such as locus of control, is not a stable attribute of the individual. Another particularity of this two-process control is that when individuals choose to fit with their environment and *go with the flow*, this is not considered uncontrollability. Instead, secondary control acknowledges that individuals can reach a sense of control through inward changes within themselves despite passive, withdrawn, or submissive behaviors. The self-oriented process of secondary control allows for acknowledging that inward efforts to compensate for failure to induce change or to enhance the value of a chosen goal is not equated with loss of control (Rothbaum et al. 1982). A balance between primary and secondary control is essential for wellbeing, although primary control has both temporal and functional primacy over secondary one (Heckhausen and Schulz 1995). In other words, individuals typically try to engage in primary control first. If they have reason not to or if they are unsuccessful, secondary control is brought to the fore. This is particularly important in organizational settings where employees feel they cannot control outcomes directly (Greenberger and Strasser 1986). The emphasis on secondary control is not to say that individuals never experience uncontrollability, but rather to point to its unstable nature since the need for control acts as a constant motivation to get out of it.

In our HiC model of adaptation, we propose that when augmented by AI, knowledge workers adapt through control-building processes. They engage in both primary and secondary controls with different emphases allocated contextually. In the words of Rothbaum (1982), "optimal adaptation is defined as the coordination of primary and secondary control" (p. 8).

HUMAN-IN-CONTROL, AN ADAPTIVE CONTROL MODEL

Our model presented in Figure 1 is built on the premise that as their work is transformed in increasingly complex ways with augmentation by AI (Benbya et al. 2020; Strich et al. 2021), knowledge workers strive to keep a sense of control. Achieving control in that regard is an adaptive process that stems from the fundamental premise that individuals adapt to their social context given past and present situations they are exposed to (Salancik and Pfeffer 1978). Knowledge workers in an organizational context of AI deployment adapt by realigning their AI-enabled work environment and themselves through primary and secondary control processes (Rothbaum et al. 1982). The starting point is a reallocation of tasks brought about by an AI deployment intended to augment the worker delegating these tasks. For delegation to lead to true collaboration and teamwork, the delegator has to rely on the delegatee for the given task, hence the important role of trust in this reliance (Castelfranchi and Falcone 1998). We therefore discuss first the relationship between trust and control. Explaining this relationship rests initially on the difference between trusting AI and trusting it to successfully complete a task.

For the purpose of our model, delegation with its accountability concerns calls on the latter one. We argue that trust can be enhanced, reduced, or complemented by direct control over the delegated task. By direct control, we mean the action of controlling elements of the task and ways of executing it (Di Nucci 2020). Delegation can only happen when some direct control is ceded and it is therefore inherently an abdication of this type of control (Baird and Maruping 2021). It consists of giving up direct control in exchange for efficiency, reduced demands, and accuracy (Boyaci et al. 2023). What is interesting in this inherent character of delegation is that relinquishing direct control can lead to the enhancement of another type of control, personal control. Reducing the *activity of controlling* can therefore lead to *being in control*. The former is purely agential and is either decreased or eliminated by delegation, whereas the latter transcends agency and is a sense of control that can be enhanced through proper delegation and the renouncing of control activities (Di Nucci 2020). The relationship between direct control and trust in AI is a dialectical one which accounts for the complexity of their mutual influence. This complexity extends to the relationship's outcome. It is not enough to decide whether to delegate or not; an important element of the dialectical process is the expectation by the human delegator as to the success of the delegation outcome (Castelfranchi and Falcone 2000). Different expectations lead the human delegator to follow different paths of control building processes, whether primary or secondary. We argue that the dialectical synthesis of trust in AI and direct control over tasks is ultimately a state of the worker's personal control that we conceive as a transient outcome of the dialectical process (Vaast and Pinsonneault 2021). We explain in this model how, even when successful at restoring personal control, some control processes can lead to an unintended reduction of the human worker while others lead to sought augmentation. Hereafter, whenever we mention control, we refer to personal control unless otherwise stated. The remainder of this section explains the HiC model starting with the dialectics of trust and control generative of a delegation expectation.

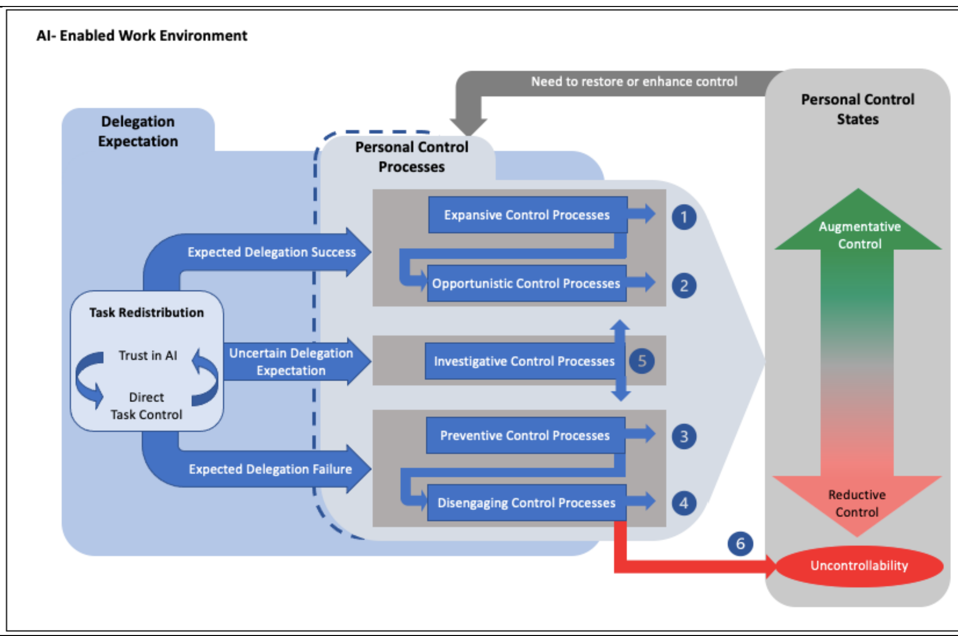

Figure 1. Human-in-Control (HiC) Model of Adaptation to an AI Work Environment

Dialectics of Trust and Direct Control

In delegation, the delegator relies on the delegatee for the performance of a task. It is this reliance dimension of delegation that confers to both trust and control a critical importance. Does the delegator trust the AI agent enough to rely on it to perform the task with little or no supervision? Or does the delegator decide to exert direct control over the task and its outcome? In this section, we argue that the two are not necessarily in opposition and that the link between them is a dialectical one. Whether and how delegation happens depends on the dialectical synthesis of trust in AI and the extent of direct control the human worker retains over the task.

Mutual influence of trust and direct control. Castefranchi and Falcone (2000) assert that “[a] good theory of trust cannot be complete without a theory of control,” (p. 799), to which we add that a good theorizing around control cannot be complete without considering trust. Trust in technology has long been recognized as essential for adoption (Komiak and Benbasat 2008) and is particularly relevant to human-AI relationships (Glikson and Woolley 2020). However, challenges to trust in AI are many, especially given the technology’s non-deterministic nature, its inherent uncertainty, and the complexity of measuring its actual performance (LeCun et al. 2015). AI carries several risks including bias, making algorithmic characteristics such as reliability and fairness important in building trust (Zhou et al. 2021) but not enough since much of the trust is not built on purely rational bases (Glikson and Woolley 2020). Many definitions of trust recognize this non-rational dimension of trust and associate trust with the absence of control (Zand 1972). We mention one that is commonly encountered in IS research where trust is "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other party will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer et al. 1995, p. 712). Trust is therefore closely linked to the action of controlling or lack of it. Notwithstanding the importance of trust for reliance on either rule-based machines or humans (Komiak and Benbasat 2008), its significance is magnified with AI, especially as the locus of control shifts from the human to the machine (Coombs et al. 2020). Understanding the relationship between direct control and trust is then core to delegation and therefore to adapting to augmentation by AI.

Intuitively, when there is trust, there is no need for direct control and delegation is the obvious conclusion, and vice versa. Direct control therefore complements trust when the latter is not high enough for the delegator to be able to rely on AI for the task. As an example, you can refuse to ride a motorcycle without a helmet because you do not trust it to be safe itself, but you might trust riding it with one. Thinking of control as a complement to trust is in line with a duality perspective of the relationship between the two. This duality is however too simplistic. In reality, the relationship as explained by Castelfranchi and Falcone (2000) is complex and far from obvious or linear. Beyond complementing trust, direct control can more interestingly change it. One direction this change can go is to enhance trust by making the AI artifact itself perceived as more reliable. Direct control can be in the ability to question and oversee the delegated task through a better understanding of the delegation process and its unfolding or, in other terms, through making the delegation less open. This is why multiple studies have associated explainable AI (XAI) with higher levels of trust (Glikson and Woolley 2020). XAI refers to simpler surrogates of complex AI models that enable the provision of limited explanations of the algorithmic output’s logic. It has even been conceived as “the ability to build confidence that AI will do the right thing in the right way at the right time” (Wixom et al. 2020, p. 12), confirming that trust increases with information sharing between the parties involved. The absence of explanations can lead to algorithmic aversion where the human ignores the machine’s recommendations even when they are accurate (Allen and Choudhury 2022). Aversion is therefore not necessarily based on outcome quality. Faced with situations of limited knowledge, people can be unduly trusting of autonomous technology. Transparency through explanations can in this case act in the opposite direction and help in lowering unrealistically high levels of initial trust (Glikson and Woolley 2020). In situations where workers tend to trust a fallible AI system, it allows them to identify the error before it impacts performance (Dellermann et al. 2019; Jussupow et al. 2021). Information sharing therefore provides grounds for human decisional understanding and potential intervention. Accordingly, algorithmic features such as explanations and transparency can contribute to trust building but do not necessarily lead to it. Indeed, transparency might have a converse effect on trust because different stakeholders trust systems differently. Generally and not just in the case of XAI, direct control can increase trust in the AI delegatee by reinforcing its reliability, but can also decrease it by undermining the AI delegatee’s abilities. In conclusion, direct control is influenced by trust and brought to the fore when complementing trust, but it also influences trust by either enhancing or reducing it.

The role of accountability. Adding to the complexity of the relationship between direct control and trust are perceptions of accountability. Since humans are responsible for the outcome of their decisions as well as those of the AI agent they delegate to, accountability concerns further stress the importance of trust. Part of the challenge to accountability is the imperfect nature of delegation to AI, which is due to responsibility assignment, but also to induced acceptance or acceptance through ignorance as many of the augmented workers lack the skills to work with AI (Willcocks 2020). Short of the ability to leverage AI for augmentation, these workers are likely to cede direct control despite high accountability.

Accordingly, the influence of high accountability on delegation does not always follow a simple intuitive logic. Typically, this influence is negative with people reluctant to delegate critical tasks and relinquish control over their outcome. This is particularly true for workers with high levels of expertise who feel greater accountability for the consequences of relying on algorithmic advice and become averse to it (Allen and Choudhury 2022). However, delegation is often welcome even when accountability is high if it is to a more efficacious other, such as a patient delegating a treatment decision to a medical doctor (Skinner 1995). Such delegation is driven by the difference in the level of expertise between delegator and delegatee. Retaining direct control in this case can sabotage the outcome, and relinquishing it is in line with one's desires of a successful delegation outcome not opposed to them, therefore resulting in personal control as per Rothbaum et al.'s (1982) definition of control as alignment. This is an example of a situation where ceding direct control to a trusted delegatee actually leads to addressing accountability and enhancing the overall sense of personal control.

Both the benefit and risk of exerting direct control to attend to accountability concerns are illustrated in the concept of human-in-the-loop that is often encountered in AI literature. Human-in-the-loop is about treating human behavior as an integral part of the augmentation system whereby people interventions can refine system outputs and result in better human-AI outcomes (Nunes et al. 2018). The aim is to keep human direct control over AI and its decisions, especially when the task outcome has important consequences. By being in the loop, humans consistently provide feedback as opposed to being excluded in a scenario of full automation. Algorithmic accuracy increases with feedback, resulting in more reliable knowledge production (van den Broek et al. 2021). Having the human-in-the-loop therefore leverages the complementarity of AI-based learning approaches and human ones and contributes to the co-evolution of humans and machines in mutual learning superior to the learning of each alone (Dellermann et al. 2019; Krakowski et al. 2023; Lyytinen et al. 2021; Rahwan et al. 2019). A legitimate question though is which learning does a human-in-the-loop improve. Tarafdar et al. (2023) suggest that there is a broken loop of learning as AI understands feedback from human task actions but is oblivious to human cognitive reactions. Learning is therefore based on partial knowledge and can be misguiding. In addition, as is the case of any direct control, a human-in-the-loop can be detrimental to performance when humans make suboptimal interventions (Ge et al. 2021) or when AI advice is sound but results in loss of unique human knowledge (Fügener et al. 2021). A human-in-the-loop configuration is therefore not sufficient to address accountability concerns but can influence them through increasing direct control.

The Dialectical Synthesis. We propose in our HiC model a dialectical process where trust and direct control are synthesized into personal control. Most IS studies adopt a conceptualization of dialectics that is inspired by the Hegelian one of thesis/antithesis/synthesis but is not strictly faithful to it, specifically when it comes to the idea of synthesis. In a recent example, the syntheses that emerge from tensions between digital technologies and occupational identity are found to be transient as the latter is constantly defined and redefined by data scientists (Vaast and Pinsonneault 2021). We adopt in this paper a similar approach and conceive personal control as a transient state that is constantly reconstructed.

According to Castelfranchi and Falcone, in addition to mutual influence, trust and direct control dialectically synthesize in a more comprehensive notion of trust. They consider Mayer's (1995) notion of trust restricted since it does not account for situatedness. It is not enough to trust AI to delegate to it, there needs to be trust in the AI agent's ability to bring to completion the task it is delegated (Castelfranchi and Falcone 2000). For this much reliance to happen, the tension between what they call core trust as in Mayer's definition, and direct control synthesizes in a belief that not only will the AI agent perform the task, but that it will perform it successfully. This dialectically synthesized and situated notion of trust is denoted global trust and extends trust to a belief that the global process of delegation will have a favorable outcome. The direct outcome of the dialectical link between trust and direct control is therefore an expectation of delegation outcome that might not necessarily lead to a delegation action (Castelfranchi and Falcone 2000). More than trusting beliefs that pertain to attributes of the trusted party namely benevolence, ability, and integrity, the willingness to rely on AI for the task is a trusting intention that indicates readiness to act on these beliefs. It is influenced by a wide range of factors encompassing these attributes, which are borrowed from human trust, as well as elements of technology trust like perceived reliability. Trusting beliefs alongside perceptions of risk and benefit drive trusting intentions (Bedué and Fritzsche 2022; Lankton et al. 2015; Mcknight et al. 2011).

Prior beliefs such as the expectation of the delegation outcome are an important factor in determining the events that follow. Several examples exist in the IS literature of psychology-based models that support the influence of prior beliefs on behavior. For instance, whether workers expect an IS event to be a threat or an opportunity influences what coping strategy they engage in (Beaudry and Pinsonneault 2005). In the context of augmentation by AI, we argue that beliefs of whether the delegation will be successful or not influence which control processes the knowledge worker employs to reach the sought sense of control. We therefore contend that the dialectical process for knowledge workers in an augmentation context does not stop at building delegation expectations. It continues in our HiC model through possibly multiple iterations of control building paths leading to the knowledge worker's state of personal control.

Personal Control Processes and States

Predicting the success or failure of delegation to AI is therefore the precursor of efforts, both behavioral and cognitive, to reach a sense of personal control. More than that, prediction is the first step in building that sense. Predicting events to succeed in them positively influences control, and predicting negative ones serves to maintain control by avoiding disappointment and salvaging the sense of effectiveness (Rothbaum et al. 1982). Subsequently, guided by the prior belief of the delegation outcome, the choice of path to a state of personal control can be one where the salient type of control is primary or secondary. While primary control is mostly action-based and secondary control mostly cognitive, it is difficult in practice to separate cognition from action which are intertwined in control efforts. Therefore, we follow Heckhausen's (1995) recommendation of differentiating the two based on their target, namely the external world for primary control and the internal self for secondary. The control processes proposed in our HiC model have a saliency of either primary or secondary control while also recognizing that people's control behavior and cognition are different with respect to a positive or a negative prediction of an event's outcome. Crossing the valence of outcome prediction with the type of control has led Bryant (1989) to suggest four control processes of primary obtaining or secondary savoring of positive outcomes and of primary avoiding or secondary coping with negative ones. He maintains that accounting for outcome expectation to subdivide control processes gives for a more granular and explanatory control model. Along these lines, we propose different primary and secondary control paths of adaptation depending on the delegation outcome expectation. However, unlike the general life context of Bryant's model, concerns of accountability raised by artifactual delegation in the organizational context lead to different primary and secondary behaviors and cognitions that we propose follow one or more of the five paths listed in Table 1 to which we add a sixth path to uncontrollability that represents the failure of all the other ones.

Personal Control Processes

Delegation Expectation \ Control Type	Primary	Secondary
Success	Expansive	Opportunistic
Uncertain	Investigative	
Failure	Preventive	Disengaging

Table 1. HiC Model's Personal Control Processes

Paths from a positive delegation outcome expectation. Changes to personal control are not necessarily triggered by a negative disruption that is associated with an unpleasant situation. They can be motivated by pleasant experiences linked to events that are perceived as positive. The misalignment between the self and the environment in this case is the result of environmental forces opening up more possibilities and pulling the worker toward higher levels of personal control. For example, When the trust level is high and AI is expected to be accurate, workers have been found to follow AI recommendations while barely applying any direct control through superficial – even sometimes absent – questioning of the AI decision rationale (Glikson and Woolley 2020; Jussupow et al. 2021; Lebovitz et al. 2022).

More personal control is associated with more choice, predictability, or responsibility. Increasing any or all will therefore eventually lead to a new alignment with enhanced personal control (Baronas and Louis 1988). We explain in the following paragraphs how paths 1 and 2 in Figure 1 enhance control through primary and secondary processes respectively. A common denominator to both these paths is an assumption of delegation grounded in the argument that a positive belief predicting a favorable delegation outcome is likely to lead to task delegation.

<u>Path 1 – Expansive control processes:</u> Some workers are more likely than others to positively enrich their jobs in response to complexity. For these workers, being augmented by an AI that learns, solves problems, and supports in complex cognitive tasks (Benbya et al. 2020), opens up opportunities for enriching and even transforming jobs. Precisely, as the machine mostly takes on routine and cognitively heavy tasks that were previously performed by the worker (Brynjolfsson and McAfee 2017), the latter can turn to higher-level activities. Time liberated by automating certain tasks can facilitate proactive innovative behavior in the form of slack resources applied to other areas (Rahrovani and Pinsonneault 2020). We argue that in applying primary control, workers who are motivated by the need to enhance their control levels tend to utilize time slack time generated by AI to expand their role and engage in more valuable work. Such control behavior is an expression of role breadth self-efficacy, "a state in which employees feel that they can take on a broader set of duties beyond their primary role" (Tang et al. 2022, p. 1025). Relieved by AI from dull tasks, they prefer to move to higher-skilled and more meaningful ones (Parker and Grote 2022). Expecting quality performance from the delegation, they are increasing their responsibilities and changing their task environment to align with their high expectation, therefore enhancing their control perception. We take the example of a radiologist relying on an AI artifact in a diagnostic task of image analysis. We assume a positive expectation of delegation involving high trust and a low need for direct control apart from validating system recommendations. As some of her time is freed up, she engages in work she considers of higher value such as collaborating with surgeons for performing interventional radiology procedures or conducting clinical research and increasing her academic production. Apart from upgrading her tasks, she is further expanding her role by collaborating with people from outside her initial circle (Tang et al. 2022). These radical changes to the work foster the co-creation of value by both the worker and the AI (Zhou et al. 2021) and therefore enhance control. Further enhancing control is the active fulfillment of positive expectations (predictive control). As such, expansive control processes lead to a state of control that we term augmentative and mean by it an alignment of the self and the AI-enabled environment at increased levels of either or all of responsibility, accuracy, skill breadth, choice of the type of performed tasks, or choice of the engaged collaborations. Such a state is conducive to augmentation where complementarity between human and machine intelligence yields better and broader results than either of the two alone (Lyytinen et al. 2021).

<u>Path 2 – Opportunistic control processes:</u> Primary control has a greater adaptive value for the individual (Heckhausen and Schulz 1995). In Figure 1, the primacy of primary control is indicated by an arrow from expansive to opportunistic control processes as the former is often tried before engaging in the latter. Along this second path, primary expansive processes have either been unsuccessfully attempted or not initiated for lack of motivation or opportunity. Secondary control in this case supports primary through either compensating for its failure or selecting a goal that increases the likelihood of its future success (Heckhausen and Schulz 1995). Since this path follows a positive delegation expectation, as with expansive processes it is typically associated with high levels of trust. Under these conditions, workers have been found to follow AI recommendations while barely applying any direct control through superficial – even sometimes absent – questioning of the AI decision rationale (Glikson and Woolley 2020; Jussupow et al. 2021; Lebovitz et al. 2022). To clarify how it differs from the primary expansive processes in path 1, we take again the example of a radiologist. Her desire to engage in clinical research is faced with a lack of research skills, which prevents her from expanding her tasks in this area. She targets the self with opportunistic control efforts by working on building the research skills needed for the new tasks. Reskilling is key for

adapting to being augmented by AI (Parker and Grote 2022) and facilitates for her the success of a potential future research activity. Other secondary control strategies that are not necessarily conscious can help her keep a positive feeling about her AI augmentation (Bryant 1989). For example, she might associate more closely with surgeons as part of vicarious control to facilitate a future involvement in interventional radiology. She can also focus on purely cognitive control efforts and think of her role as a supervisory one where she is responsible for ensuring the quality of the final diagnoses rather than performing the analysis herself. Adjusting her desire from either increasing research production or starting surgical interventions to improving diagnostic productivity can be achieved by convincing herself that a better use of the AI-generated slack time is to work through the high load of piling diagnostic tasks. In all these cases, the radiologist is adapting through bringing her self – skills or desires – in line with environmental forces.

Assuming no major flaws in the delegation outcomes – a possibility that we discuss as part of the feedback loop of the HiC process – opportunistic control processes can lead to better accuracy and higher efficiency. Knowledge workers engaging in this path are relieved from the burden of routine tasks (Autor 2015). Instead of going through laborious direct control efforts, they are satisfied with output validation that could be as simple as asking a colleague's opinion (Anthony 2021). Armed with a trusted AI advisor, they are likely to make more accurate decisions in the tasks that are part of their traditional role before augmentation, therefore exhibiting higher dedication to their in-role responsibilities (Tang et al. 2022). At the least, they are able to achieve a larger number of tasks than pre-augmentation and gain control through reducing overload (Barley et al. 2011). We call this path opportunistic due to control enhancement that is directed inward in the form of improving one's own comfort, skills, or accuracy, unlike expansive efforts that enhance control while enriching the job. As pointed out in Rothbaum's (1982) model, the difference between the two paths is one of emphasis, and job enrichment is likely to be accompanied by self-oriented gains as well for workers. While still conducive to the augmentation of the individual, the opportunistic processes' inward emphasis leads to a control state that is less augmentative than expansive processes.

Paths from a negative delegation outcome expectation. Unlike the pleasant trigger of the first two paths, paths 3 and 4 are driven by an expectation that delegation will produce unreliable outcomes. This represents an imbalance between the desired and the expected and threatens knowledge workers' accountability thus disrupting their sense of control. We see that even though control is not mentioned, this disruption manifests in the literature such as when radiologists experienced increased levels of uncertainty and expressed confusion and frustration when augmented by AI (Lebovitz et al. 2022). The paths discussed here are therefore ones that primarily attempt to restore control rather than enhance it.

Path 3 – Preventive control processes: When control is unbalanced with a misalignment between self and environment, the type of reaction is largely influenced by the source of this imbalance (Greenberger and Strasser 1986). We argue that this primary control path is engaged when that source is the AI agent. Beliefs of the unreliability of the delegatee, in this case, are caused by distrust amplified by accountability concerns. We follow scholars who differentiated distrust from trust, as the latter deals not with the absence of beneficial conduct, but with the presence of a harmful one (Komiak and Benbasat 2008). One way knowledge workers can prevent the expected harm is through enacting workarounds (Azad and King 2008). When the AI output is an untrustworthy recommendation harm prevention can be through ignoring it or at least retaining a high degree of direct control over the task. Delegation action is therefore either inexistent or partial in such conditions. Specifically, AI systems can outperform humans in capturing the know-what aspects of knowledge but overstating their objective truth risks undermining the rich know-how of experts necessary for handling uncertainty when making a judgement (Lebovitz et al. 2021). Experts who rely on this know-how are averse to relying on machine recommendations, especially when these recommendations are based on obscure grounds (Allen and Choudhury 2022). Distrust can therefore be beneficial for preventing a potential error in judgment. What is needed in augmentation contexts is a balance between leveraging AI's capabilities and over-relying on it (Dellermann et al. 2019). This path brings to the fore the role of humans in compensating for machine errors (Jussupow et al. 2021). As an example, when presented with an AI assessment of a tumor as benign, a radiologist performs herself the image analysis with disregard to the AI. Considering it untrustworthy, she relies on her own skills and knowledge to avoid a potential false negative diagnosis that puts at risk the patient's life.

Another reason for engaging in preventive control processes even if the AI agent is considered trustworthy is fear of increased work which gives rise to ignoring algorithmic advice (Kawaguchi 2021). This can be particularly relevant in contexts of high workload where paradoxically augmentation is the most needed

(Boyaci et al. 2023). In either case, knowledge workers in this path do not benefit from slack resources in this path. The control state they reach is likely to be restored close to prior levels or even less. The latter is a risk when the activity of controlling the AI consumes resources that could otherwise be used for performing tasks – automated or not – comprised in the job. Primary control efforts might therefore succeed at aligning the self and the work environment, but this is likely to be at lower levels of control.

Path 4 – Disengaging control processes: In their simplest description, disengaging control processes are about giving in to an unpleasant situation. More specifically, when the source of control imbalance is the AI agent's lack of reliability, disengaging control processes typically compensate for failed primary preventive ones that are more effective at attending to accountability. However, this secondary control path can also be started with no prior pass at primary control. Here, disengagement can indicate a temporary state of uncontrollability or possibly serve as an attempt to reserve the worker's energy and emotional investment for other areas where they can be of use (Rothbaum et al. 1982). Despite the stickiness of actual accountability, disengagement serves to reduce perceived accountability by distancing oneself from the decision when negative outcomes are expected (Bushardt et al. 1991). Later iterations possibly benefit from disengagement as one recollects to re-engage in primary control efforts or reconsiders trusting AI. We conceive disengaging control processes as the least implicated and diligent ones and often a last resort to reach alignment of self and environment. Their starting point of negative prediction of delegation is a step in the control process as a form of predictive control. It is an often conscious avoidance of disappointment where individuals who have faced multiple failures either avoid tasks or expend minimal effort in executing them (Rothbaum et al. 1982). Therefore, in both compensatory and goal selectivity cases, the worker can disengage actively in terms of ignoring AI's outcomes, or cognitively in terms of dissociating mentally from augmentation. The latter is a form of control that is highly withdrawn and passive. This path acknowledges that while some workers perceive augmentation as a source of stimulation, others live it as a taxing job demand (Parker and Grote 2022). Instead of the intended augmentation, they could experience negative complementarity between humans and AI (Shrestha et al. 2019) and unintended reduction through the depletion of unique human knowledge (Fügener et al. 2021). The control state this path leads to is typically an alignment involving reduced responsibilities, role, performance, or even skills. We refer to this state as reductive control.

Several scenarios are possible along this path, most of which are cognitive in nature; we illustrate a few through an example. For a customer service representative, there might not be alternatives to collaborating with the AI agent which prioritizes incoming cases. He attends to cases in the order of prioritization fed by AI into his system and showing on his screen. Believing the prioritizing AI to be unreliable, he still follows its recommendation for lack of knowledge of how to decide on the order otherwise. This means that delegation happens despite a low trust level, a low degree of direct control, and expectations of delegation failure. Short of changing the AI recommended order, he shares his worries with his manager and relays her comments to the rest of the team. By associating with a more powerful other, and although the situation is not rectified, he still gains vicarious control. Additionally, he convinces himself that his job is to serve customers regardless of case importance, which is the responsibility of the IT department deploying the AI. Through interpretive control, he solves the accountability problem by decreasing the perception of his responsibilities. This type of control process can go further in justifying the unpleasant situation. For instance, if that worker gets demoted after consistently bad customer ratings, he might consider it an opportunity for more autonomy, or reposition his need for control to lower levels (Greenberger and Strasser 1986). He therefore reaches control alignment at lower levels of either responsibilities or need for control. We call this state reductive control as it holds a strong risk of reducing the person's role and scope of job.

Path from an uncertain delegation expectation. When knowledge workers are not sure about the delegation outcome, they tend to exert heavy cognitive efforts in their decision-making process (Boyaci et al. 2023). The fifth path in Figure 1 is one of primary control where the worker questions the decision or recommendation of the AI agent and exerts direct control over it while delegating it partially.

Path 5 – Investigative control processes: More often than not, AI and human judgment diverge (Lebovitz et al. 2022) and the trust level is not at an extreme that propels the delegation expectation in positive or negative paths. In this situation and when accountability is high, workers feel the need to investigate the AI agent's recommendations before relying on them. A risk if the trust level is not high enough is that workers might spend more effort in resolving a conflict between their judgment and that of the machine than in finding alternative actions (Coombs et al. 2020). However necessary sometimes, investigative efforts counter the benefit of task time reduction and cognitive relief that augmentation by AI is expected to provide. Even more, it can lead to cognitive overload and inefficiency (Boyaci et al. 2023), especially for conscientious employees who are used to orderly ways of working (Tang et al. 2022). Whether the machine is an XAI agent with limited explanations or an opaque one, workers engage in validating practices to make sure its output is trustworthy (Anthony 2021). Examples in the literature of investigative processes are many. We mention two of them. In Lebovitz et al.'s (2022) study, radiologists diagnosing lung cancer used AI interrogation practices to reduce uncertainty as to the machine's accuracy and relate their knowledge claims to those of AI. Example practices were reexamining the image while changing the contrast settings and enacting other image manipulations. In another study by Anthony (2021), junior bankers engaged in validating practices for machine-generated financial analysis. Those included establishing reliability, assessing accuracy, and correcting analysis. Co-constructing these practices with senior bankers resulted in learning for junior bankers who developed expertise important for their career.

We conceive investigative control processes as supporting processes for the previous four rather than standalone processes in our model. After validating the financial analysis and finding it trustworthy, junior bankers can continue with expanding practices especially since they are better equipped now in knowledge and expertise for doing more valuable work. In an opposite example, radiologists who consistently do not trust AI's diagnosis decide to stop investigating and wasting their time, and instead prefer to ignore the AI in a preventive control process. In other words, eventually, the workers learn through investigative processes and are therefore able to form a less uncertain expectation of the delegation success. Through that, they move to other control processes in building their control perception.

Path to uncontrollability. We label this path as the sixth in Figure 1 for explanatory reasons; however, it is less of a path and more of a failed set of paths. Indeed, we expect uncontrollability to be reached after multiple attempts at other paths. In fact, any failed control building attempt is a risk of uncontrollability. Still, the most likely and most direct link is with disengaging control processes, since these are the last resort when all else is either not possible or not working. When disengaging control processes fail at achieving a state of control even a reduced one, continued misalignment will then result in a transient state of uncontrollability. We argue that this state is not a sustainable one as the need for control is too deeply rooted (Greenberger and Strasser 1986; Leotti et al. 2010; Rothbaum et al. 1982) to allow its constancy.

A Transient Dialectical Synthesis

Our proposed HiC model has two types of feedback loops that are represented in Figure 1 by a dotted line and block arrow respectively. The first is continuous and happens at the interface of control states and both the AI-enabled work environment and the delegation expectations and the second is discontinuous at the interface of control states and control processes.

Control processes, especially primary ones, change the environment. On the other hand, environmental forces enable or constrain certain behaviors and induce cognitions, thereby directly influencing these processes and, through them, the knowledge worker's delegation expectation. In other words, control processes unfold an experience the worker has with the work environment, which constantly updates delegation expectations. We conceive this interface experience as liminal, where "liminality is produced by the copresence of multiple, distinctively different forces and potentialities that shape human experience, the balance of which is a state of emergence marked by ambiguity and multifariousness" (Zhang et al. 2021, p. 1197). The feedback at this interface is therefore in constant construction as the worker engages in the control processes. The continuous nature is represented by a dotted border of the control processes in Figure 1 similar to a permeable membrane. As workers perform behaviors or build cognitions throughout the process, they are continuously exposed to cues from the environment which they use to construct and interpret events (Salancik and Pfeffer 1978). In doing so, their trust in AI and their need for personal control might change. Trust is known to be fragile, especially following its initial formation (Kim et al. 2004). In the example of the radiologist, assuming she was engaging in opportunistic control processes, this can be in the form of a conflicting diagnosis she receives from the machine. This environmental cue is likely to interrupt the opportunistic process and warrant the radiologist to reconsider her trust in AI and her need to exert more direct control. If her updated delegation predictions are much more negative, preventive processes are more likely to prevail. It is important to note here that while the feedback experience is liminal and both the environmental influence and the update of the delegation expectations are continuous, the opposite direction from delegation expectations to control processes is not. Indeed, predictions of delegation success are constantly updated through the worker's experience with the environment, whether in terms of tasks performed, collaborations enhanced or reduced, or other environmental elements. However, delegation expectations change the choice of control processes along the adaptive path only when the balance between trust and direct control crosses a certain threshold. Not every experience the worker has with AI is likely to change that balance. In the presence of unpleasant experiences, "(direct) control is exercised by means of thresholds which may not be crossed without the withdrawal of trust" (Luhmann 1979, p. 29). A radiologist engaged in opportunistic control processes might not change her behavior the first time she encounters a flawed diagnosis. While she could be slightly more skeptical of the AI, the change might not be enough to warrant altered behavior. Multiple occurrences are likely to be needed before her delegation expectation threshold shifts away from positive. For clarity, the block arrow in Figure 1 refers to discontinuous developments in the process while the dotted line represents continuous influence.

The other type of feedback in the HiC model is discontinuous. It is triggered by the need to change from one state of (non)control to another. In the extreme case, once a state of uncontrollability is reached, the worker will inherently reattempt to gain control and persist in those attempts until a balance is reached in control perception (Greenberger and Strasser 1986; Rothbaum et al. 1982). Reattempting one or more control processes might, through the liminal feedback loop that is constantly activated, change the worker's prediction of the delegation outcome and therefore the alternative control paths which that worker can engage in. Similarly, and since different people have needs for different degrees of control, someone who is in a state of reductive control might reattempt to gain more control through new process passes.

Feedback is not solely meant to change a process outcome; it can also reinforce it. When following a path with expansive control processes for instance, delegating tasks and co-creating services with the machine increase the sense of ownership and subsequently trust in the AI agent (Dellermann et al. 2019), leading to more reliance on the AI agent and more opportunity for growth for the worker. Opposed to this virtuous cycle is a vicious one for a worker who predicts delegation failure and reaches a control state on the reductive side of the continuum. Especially when this state is reached after multiple failures, the worker might doubt the task controllability or their own efficacy, leading to even lower levels of control. Indeed, expecting failure can lead to envisioning it and ruminating about its consequences, which consumes the brain's limited capacities and deters it from implementing remedial action (Skinner 1995). The worker is caught in a vicious cycle of lowering both control expectations and perceptions, possibly reaching uncontrollability.

In short, feedback leads to either changing or reinforcing control states. HiC iterations through feedback loops therefore make for transient control states. Many factors contribute to state instability, whether internal to the worker or external in the environment including the AI agent and its behavior. The dialectical process that links trust in AI and direct control over the automated tasks therefore synthesizes in transient control states that change through control processes driven by expectations of delegation success.

Contributions to Research

With AI's paradigmatic technological change, new theories are needed to explain how people work with the machine (Lyytinen et al. 2021). Our HiC model represents an important step in this direction by bringing to the fore a human-centric and job-encompassing model of adaptation to a work environment of augmentation by AI. While many studies have been published about the outcomes of augmentation (e.g., Fügener et al., 2022), little has been written about how it unfolds in practice, especially outside the realm of delegated tasks. In widening the scope of adaptation, we contribute to the AI augmentation literature by introducing personal control as an adaptive process. With regard to adaptation, extant augmentation literature has investigated workers' decision-making processes in situations of agreement or disagreement with the AI (Jussupow et al. 2021; Lebovitz et al. 2022), their coping mechanisms (Chen et al. 2022), and the cognitive effort needed for adapting to the new augmentation (Boyaci et al. 2023). We complement this emphasis on direct adaptation manifestations in the literature with personal control, which extends adaptation to both direct and indirect behaviors and cognitions. We also contribute to the literature on trust in technology as we bring to the fore the nuanced complexity of the relationship between trust and direct control (Castelfranchi and Falcone 1998, 2000) and how this relationship influences delegation behavior. We mention these two contributions as the salient ones while highlighting that personal control is pervasive in that it influences adaptation as well as other interrelated phenomena. Therefore, the HiC model can also contribute through guiding research inquiry in these realms, which we delve into in the next paragraph.

Avenues for Future Research

Following is a non-exhaustive compilation of potential avenues for future research.

First, researchers can build on the HiC model to understand, interpret, or even predict if and how augmentation is achieved for knowledge workers at the individual level, and identify patterns of control processes at the group level. This would answer calls for practically relevant AI research (Agerfalk 2020) by providing managers with guidance to facilitate desirable adaptation behaviors and avoid others.

Second, through empirically observing how individual knowledge workers follow control paths, researchers can have a better understanding of how digital transformation emerges in a bottom-up direction. Workers' adaptive control behaviors might not change the organizational system themselves, but the human-technology configurations that emerge from their choices of control paths can lead to an understanding of second and third order effects of digital transformation. These involve respectively transformed patterns of work and reshaped nature of work and organizational structures (Baptista et al. 2020).

Third, our model draws on delegation with an assumption of a certain level of stability in the intended division of labor between humans and machines. We suggest that future research consider a dynamic allocation of tasks between the two. In an uncertain environment characterized by high task complexity, a static outlook on delegation can be difficult, and dividing tasks dynamically is more realistic (Abbass 2019). This can extend into research exploring different types of trust influencing delegation, such as emotional and cognitive (Glikson and Woolley 2020). A trust emphasis can inform questions on how the delegation success expectation is formed, how the threshold at which it changes is determined, and whether the model behaves differently in situations of trust or distrust.

Fourth, the control perspective we propose is one that is personal and where an individual aligns environment and self to deal with the job transformative consequences of augmentation by AI. A different but complementary control perspective, algorithmic control, is increasingly attracting attention in IS research. It is a technology-mediated action exercised by organizations and platforms over their workers (Kellogg et al. 2020) and is highly pertinent when considering control directed toward others. Our HiC model can be used to explain adaptation to algorithmic control, not just to augmentation. Example questions are how different algorithmic control strategies influence the workers' control processes and how a balance of the two types of control can co-create value for both workers and organizations.

Fifth, since the engagement in a control process is contingent on the relationship between trust in AI and direct control over the task, research can build on the HiC model to investigate factors impacting each. Several possibilities can be explored such as the nature of the automated tasks, the workers' attributes, and the nature of the AI system. The complexity of tasks and the criticality of their consequences for instance play an important role in delegation (Lebovitz et al. 2022). For workers, different contexts, hierarchical levels, and personal attributes can explain differences in control process patterns. As to technology, an area that directly relates to our model is explainability. Beyond promoting trust, explanations might enable or impede certain control paths, especially since they differ in how, how much, and in which way they are delivered (Agerfalk et al. 2021). Accounting for those nuances enriches our understanding of adaptation to augmentation and allows contextualized empirical studying of control processes.

Finally, engaging in control processes brings about changes to automated and unautomated tasks, job scope, and other job elements such as roles and cognitions. This makes a work design perspective particularly valuable for studying augmentation by AI (Parker and Grote 2022). As augmentation is likely to transform jobs, managers including human resource managers play an important role in this work redesign, but this is only part of the real transformation. The HiC model provides a theoretical foundation for bringing to light an often hidden side of this design, one that is initiated by the workers themselves who craft their jobs by altering their tasks, relations, and job cognition (Wrzesniewski and Dutton 2001).

Conclusion

Augmentation success is often jeopardized less by algorithmic reasons and more by the challenge of integrating AI into the broader sociotechnical system. It is therefore of critical importance to offer a human-centered theoretical perspective of how knowledge workers adapt to augmentation and guide both research and practice in navigating its sociotechnical unfolding. In HiC, we propose a theoretical model to explain how these workers adapt through primary and secondary control not only to the deployed AI system(s) but also more importantly to the resulting changes in their work environment. Task redistribution is the most direct change and a starting point where workers develop dynamic trust beliefs and either cede direct control over a task through delegation or retain some or all of it, both in an effort to reach a general sense of personal control. The whole job emphasis and personal control perspective we adopted are likely to take more importance in the future as the AI turns into multiple embedded AIs and the range of automated tasks keeps widening.

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