

# Human-in-Control: A Human-Centered Model of Adaptation to AI Augmentation

*Rania Afiouni, McGill University, rania.afiouni@mail.mcgill.ca*  
*Alain Pinsonneault, McGill University, alain.pinsonneault@mcgill.ca*

## Introduction

With Artificial Intelligence (AI), technology is shifting from assisting knowledge workers to augmenting them (Jain et al., 2021). The change for these workers is significant and unprecedented as they find themselves working alongside smart machines (Coombs et al., 2020). As they change the way they conduct business day-to-day, they are severed from familiar ways of maintaining control over their work, which threatens their overall sense of control. The relevance of control to augmentation stems from the nature of AI. First, AI threatens personal control through its opacity, which hinders human understanding of its decision's rationale (Burrell, 2016). Second, AI is capable of autonomous behavior (Rahwan et al., 2019). However, its autonomy entails neither consciousness nor responsibility (Agerfalk, 2020), rendering knowledge workers accountable for the outcomes of machines that think, learn, develop intentions, lack transparency, and exhibit a dynamic behavior. We argue in this paper that this disrupts their personal control, and that they adapt by seeking new ways to maintain it.

Control has been largely absent from extant adaptation models, except as a precursor of coping behavior and cognition (Beaudry & Pinsonneault, 2005) rather than a goal of adaptation. In an augmentation context, coping mechanisms aim to better leverage the use of AI (Chen et al., n.d.). There is therefore an assumption that workers are users of a technological tool rather than delegators to an autonomous agent (Baird & Maruping, 2021), which keeps coping and adaptation efforts in the vicinity of the automated tasks. This emphasis on changes happening around AI-altered tasks is also present in augmentation studies addressing adaptation to opacity of AI (Anthony, 2021; Jussupow et al., 2021; Lebovitz et al., 2022). These studies provide valuable insight into how knowledge workers interact with AI and react to it. However, augmentation could mean decisions made or recommended without necessarily an artifact being used or interacted with. Accordingly, we argue that we need to move the adaptation discussion away from the technology and widen its radius as concerns of a delegation that transforms jobs are also felt outside the realm of automated tasks. The Human-in-Control (HiC) model that we propose explains adaptation as a process where delegation perception leads to control through changes to both the self and the AI-enabled work environment.

Bringing control to the fore of the augmentation conversation places the human at its center and recognizes that AI's profoundly disruptive nature (Benbya et al., 2020) has effects that include behaviors outside use interactions and across the whole job. In this

conceptual paper, we propose the HiC model in figure 1 as a process through which individual workers reconstruct their general sense of control at work. To our knowledge, this is the first study that introduces personal control as an adaptive process. We present a new perspective of adaptation as a control phenomenon that encompasses multiple aspects of the job, therefore avoiding a myopic understanding of adaptation to augmentation.

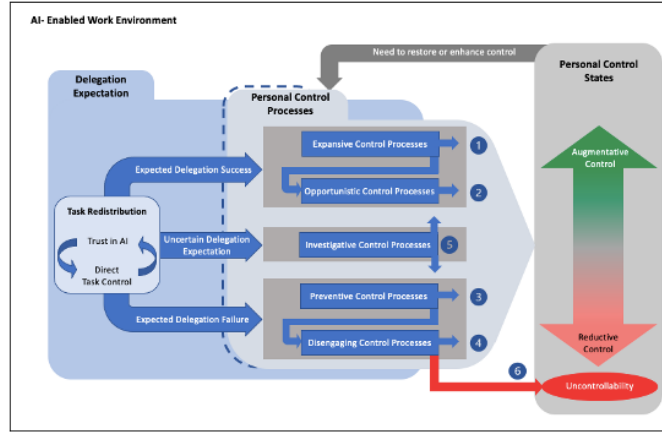


Figure 1. Human-in-Control (HiC) Model of Adaptation to an AI-Enabled Environment

## Background Theories

We draw our background theories from delegation and control. We argue delegation is essential for understanding adaptation to augmentation through personal control.

### Delegation

We follow Baird and Maruping's (2021) recommendation to study delegation rather than use of AI. The core of augmentation is the redistribution of work between humans and machines, allocating to each what they do best (von Krogh, 2018). In this redistribution, delegating tasks frees the delegator for other work and can result in better performance (Fügener et al., 2022). However, only responsibilities for task execution, not outcome, are transferred to the delegatee. Control is relevant to delegation due to this separation between execution and responsibility as well as for the intricacies that differentiate human and non-human delegates. Indeed, AI cannot deliver on ethical judgment, symbolic reasoning, or social management (Agrawal et al., 2018) and is not as communicative of how it is performing a task as a human could be (Burrell, 2016). These idiosyncrasies of delegation to AI have implications on the human's personal control.

### Personal Control

Personal control is an innate psychological necessity for every human being. The need for control is therefore desirable and people naturally try to increase their personal control. However, the perception of personal control is influenced by personal experience and learning (Leotti et al., 2010). 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 primary control process brings the environment into line with one's wishes, and the secondary one refocuses the change efforts on the self to bring it into line with environmental forces. Secondary control acknowledges that inward efforts either to compensate for failure to induce change or to enhance the value of a chosen goal are not equated with loss of control. The two processes are intertwined, and the difference is one of emphasis, with primary having primacy over secondary.

### **Human-in-Control (HiC) Model**

We propose that augmented knowledge workers adapt by realigning their AI-enabled work environment and themselves. Our model is divided in three components. In the first one, the worker's expectation of delegation success is the synthesis of a dialectical relationship between trust in the AI agent and direct control over the automated task (Castelfranchi & Falcone, 2000). We differentiate between direct and personal control. The former is a purely agential *action of controlling* and is either decreased or eliminated by delegation, whereas the latter transcends agency and is a sense of *being in control* that can be enhanced by renouncing control activities through delegation (Di Nucci, 2020). Direct control is intuitively antagonistic to trust but can also conversely strengthen it. The complexity of balancing direct control and trust is further enhanced by accountability concerns. This balance eventually results in a delegation decision. However, it is not enough to decide whether to delegate or not; an important element of the process is the delegator's expectation of delegation success (Castelfranchi & Falcone, 2000). Different expectations lead the worker to apply different control building processes.

The second component is therefore the control processes leading to the third component, control states. Different processes are issue from positive, negative, or uncertain delegation expectation. When positive, change to personal control is triggered by pleasant experiences rather than a negative disruption. The misalignment between self and environment is the result of environmental forces pulling the worker toward higher levels of personal control. Two processes are proposed. In the first, workers engaging in primary *expansive control* delegate routine and cognitively heavy tasks to the machine, therefore benefiting from slack resources to engage in innovative activities (Rahrovani & Pinsonneault, 2020). They utilize time slack to expand their role and engage in more valuable work resulting in an enhanced control state that we refer to as augmentative. Augmentative control aligns self and environment at increased levels of responsibility, accuracy, skill breadth, choice of tasks, or choice of collaborations. In the second process, primary expansive control has either been unsuccessful or uninitiated for lack of motivation or opportunity. Armed with a trusted AI advisor, workers might build skills in preparation for future expansive efforts or perform better in tasks that are part of their traditional role. We refer to secondary *opportunistic control* due to control enhancement being directed inward at improving one's comfort, skills, or performance unlike expansive efforts that enhance control while enriching the job.

When delegation expectation is negative, there is an imbalance between the desired and

the expected which threatens knowledge workers' accountability, thus disrupting their sense of control. Two processes are proposed. Primary *preventive control* is engaged when beliefs of unreliability of the AI agent lead to harm prevention through either ignoring AI's recommendation or at least retaining a high degree of direct control over the task, bringing to the fore the role of humans in compensating for machine errors and fear of increased work (Jussupow et al., 2021). In the absence of slack resources, workers are likely to restore control to prior levels or even less. On the other hand, workers engaging in secondary *disengaging control* give in to an unpleasant situation and reduce perceived accountability through distancing themselves from the decision when negative outcomes are expected (Bushardt et al., 1991). This process is proposed as a last resort for aligning the self and the environment. The control state it leads to is typically an alignment involving reduced role, responsibilities, performance, or skills. We refer to this state as reductive control. When disengaging control fails at achieving even a reduced control state, continued misalignment will then result in a transient state of *uncontrollability*. We argue that this state is not sustainable as the need for control is too deep to allow its constancy (Rothbaum et al., 1982).

Lastly, delegation expectations can be uncertain with no clear valence, in which case we argue that workers engage in primary *investigative control*. They question the decision or recommendation of the AI agent and exert direct control over it while delegating it partially. Consequently, they exert heavy cognitive efforts in their decision-making process. Eventually, they learn through investigation and are able to form a clearer delegation expectation. Consequently, they move to other control processes. Our model is anything but linear. We propose two feedback loops, a continuous one (dotted line in figure 1) that happens at the interface of control states and both the AI-enabled work environment and the delegation expectations, and a discontinuous one at the interface of control states and control processes. Feedback leads to reinforcing or changing control states. Therefore, the dialectical synthesis of trust in AI and direct control over tasks is ultimately a state of the knowledge worker's personal control that is a transient and constantly reconstructed outcome of the dialectical process (Vaast & Pinsonneault, 2021).

The aim of our HiC model is to provide a theoretical basis for empirical research investigating job-wide rather than task reactive adaptation. Our main contribution is in presenting a new perspective of adaptation as a control phenomenon that encompasses multiple aspects of the job in response to a changed AI-enabled work environment.

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