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ABSTRACT:
Advances in AI technology affect knowledge work in diverse fields, including healthcare, engineering, and management. Although automation and machine support can increase efficiency and lower costs, it can also, as an unintended consequence, deskill workers, who lose valuable skills that would otherwise be maintained as part of their daily work. Such deskilling has a wide range of negative effects on multiple stakeholders — employees, organizations, and society at large. This essay discusses deskilling in the age of AI on three levels - individual, organizational and societal. Deskilling is furthermore analyzed through the lens of four different levels of human-AI configurations and we argue that one of them, Hybrid Intelligence, could be particularly suitable to help manage the risk of deskilling human experts. Hybrid Intelligence system design and implementation can explicitly take such risks into account and instead foster upskilling of workers. Hybrid Intelligence may thus, in the long run, lower costs and improve performance and job satisfaction, as well as prevent management from creating unintended organization-wide deskilling.

Deskilling, Upskilling, and Reskilling: a Case for Hybrid Intelligence

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1. INTRODUCTION

Over the past two centuries, technological and organizational innovations have repeatedly brought immense changes to the labor market. Major transformations include industrialization followed by automation and robotics, and finally a digital transformation. The digital transformation started with the advent of personal computers and in recent years continued with the deployment of "intelligent" systems involving some form of Artificial Intelligence (AI). Here, we will first examine labor market changes with respect to deskilling and then dive deeper into this concept with respect to AI.

Although contemporary understanding of deskilling has multiple interpretations, generally it describes the loss of professional skills due to technological or work practice changes. Examples of such skills include decision-making and judgement skills lost due to work management (Davis, 2008) as well as psychomotor and cognitive skills (Ferris et al., 2010). The term was conceived during industrialization, as capitalist modes of production separated the conceptual and skilled part of a task from the execution of the task (Sutton, 2018). This macroeconomic trend reduced immediate costs through replacing a minority group of highly skilled workers with a cheaper, rapidly expanding un- or low-skilled urban, industrial workforce (Braverman, 1998). This trend also resulted in the deconstruction of craftsmanship. For instance, in the 19th and first half of the 20th century, the general shift from small-scale artisan production to factory work such as the introduction of the mechanical loom led to the replacement of highly-skilled artisans by unskilled factory workers (Brugger & Gehrke, 2018). In this process, the creation of fabrics was standardized and the fabric design and material choice became centrally dictated. This separation of production and design led to fundamental changes to the nature of the work and simplification of tasks: unskilled people could accomplish the tasks, but were unable to design and produce fabric without the factory system support, an example of deskilling. In parallel, industrialization combined with optimization of organizational processes brought about the assembly line paradigm, which both revolutionized traditional areas like meat-production (Nibert, 2011) and enabled mass production of modern equipment such as the automobile. An important caveat of these early examples of sectoral deskilling is that a few skilled employees remained to manage, or design and construct machinery that replaced other parts of the labor process. These highly trained employees formed the seed of the increasingly dominant knowledge workers[1] of the 21st century.

Historically, shifts in the workplace often occur in tandem with technological development. In the second half of the 20th century, the introduction of production line robotics as well as general advances in machine automation induced significant job replacement. This set in motion a growing divide between low-skilled jobs dedicated to operating the machinery and high-skilled jobs responsible for interaction with and defining the roles of the machinery (Cabitza, Rasoini and Gensini, 2017; Gasparetto and Scalera, 2019). In the same period, digital advances, primarily revolving around the introduction of the workplace computer, catalyzed a fundamental transformation of the landscape of work through the large-scale emergence of the knowledge worker areas as distinct as finance (Dilla & Stone, 1997; Sutton, 1993; Sutton et al., 2018) and medicine (Hoff, 2011; Rinard, 1996). An example of the transition can be seen in word-processing, where the word processing specialist in the 1980s was replaced by word processing software. Using such software became a common skill, integrated in elementary schools in the 1990s. This trend has continued in the 2000s with increasing degrees of workplace digitization. Since the mid-2010s, the world has been at the brink of a significant job market transition as deep learning technologies (LeCun et al., 2015) are finally starting to fulfill some long-standing promises of AI. In particular, using algorithms trained on large amounts of data, AI is now able to perform more complex tasks (McAfee & Brynjolfsson, 2017) and thus increasingly enters the domain of knowledge workers (Frey & Osborne, 2013; Davenport & Ronanki, 2018).

Technologically induced deskilling can be understood from an individual perspective; however, this effect is rarely isolated to the individual, and more often than not includes implications for organizations and society as well (Stone et al., 2007). Together, these three perspectives provide a holistic approach for researchers and corporate strategists to assess the potential for deskilling, upskilling or reskilling when developing AI systems. Adding to previous literature, we here introduce the concept of Hybrid Intelligence (Dellermann et al., 2019, Dellermann 2020), which explicitly considers the impact of AI on human actors, and suggests specific strategies for designing and implementing sociotechnical systems that incorporate AI to the benefit of human participants.

At the society level, deskilling is continually framed as an economic issue for governments and institutions. This has repeatedly fuelled concern about technologically induced unemployment, in the sense of permanent reduction in the active labor force. Despite these fears and the clear sectoral workforce changes discussed above, we have not experienced a trend of growing unemployment rates. In particular, Feldmann (2013) found the macroeconomic effects of technologically induced unemployment to be temporary,

1 An employee whose primary contribution to the workplace is knowledge of a specific subject, e.g., physicians academics, engineers, architects (Davenport, 2005)

with work moving from areas replaced by technology to producers of that technology within three years' time. Thus, historically, the introduction of new technologies increases the knowledge level in the general workforce, despite temporary periods of job loss and deskilling. Although market forces seem to facilitate a rather fast bounce-back on average, there may of course be larger variances in the resilience of different societies and nations. Maximizing benefits and minimizing negative implications from technological advances therefore remains a permanent center point of legislative attention. As an example, to address this, Kim, Kim and Lee (2017) find that "legal and social limitations on computerization are key to ensuring an economically viable future for humanity" (p. 7). Additionally, the ongoing and expected changes to the job market have naturally spurred parallel intense discussions of the reframing of the educational system to bridge the future "skills gap" (Chrisinger, 2019; Jerald, 2009; Tuomi, 2018).

Recently both researchers (Harari, 2017; Korinek & Stiglitz, 2019; Makridakis, 2018; Pol & Revely, 2017) and intergovernmental agencies (Council of Europe, 2019; Schwab & Davis, 2018) warned of the possibility that the large-scale deployment of AI-based technologies may indeed defy historical trends and introduce permanent macroeconomic unemployment. While the potential long term consequences for humanity are hotly debated, there is a growing consensus that development and application of AI will indeed cause radical changes to the job market as a whole and that all occupations will be affected in one way or the other (Chrisinger, 2019). In short, the current consensus is that everyone will have to adapt their work skills in response to AI implementations.

At the individual level, technological changes often bring about dramatic shifts in the skills and abilities necessary to navigate both our personal and professional lives. Along the lines of the former, Wilmer et al. (2017) describe the impact of using smartphones and related mobile technologies, where "habitual involvement with these devices may have a negative and lasting impact on users' ability to think, remember, pay attention, and regulate emotion" (p. 1). Similarly, human users of search engines experience a decreased mental capability to store information, even though they simultaneously develop the ability to store how to find that information. In what is known as the Google-effect, memory capability is reallocated from storing facts to storing search strategies (Sparrow, Liu, and Wegner, 2011). These types of technological adaptation can sometimes result in an over-reliance on technological assistance. As discussed below, deskilling at the individual level often occurs in organizations when management applies digital technologies and robotics without reflection as to their effects on the workforce and human roles in the organization (Hutchins, 1995) .

At the organizational level, one framework of particular relevance to deskilling in the age of AI is that of technological dominance (Sutton, 1998; Sutton and Arnold, 2018) because technology can increasingly be understood as an actor in the work process. This theory focuses on systems made for assisting professionals in their decision process, and explains the risk of overreliance on such technology (Ferris et al., 2010). The likelihood of overreliance largely depends on i) the user's experience level, ii) problem complexity, iii) user's familiarity with the systems and iv) the user's cognitive fit with the system's underlying decision processes (Sutton, 2018).

In their research, (Hoff, 2011) observed that unintended deskilling often occurs when the goal of the technology is to reduce costs and increase productivity by minimizing human input where possible and automating work. This process raises the pertinent question, how to structure human-AI interaction in corporate settings. The required insights can, however, only be achieved if the skills of the future are thoroughly understood. We must also understand how the skills of the future come into play in the concrete interaction between AI-driven systems and humans. To investigate this, we revisit the concept of deskilling through the lens of a particular type of human-AI interaction, what we call Hybrid Intelligence (Dellermann et al., 2019). We do this in order to:

a) highlight the risks of deskilling due to the overreliance, technological dominance and lack of sustainability when establishing Human-AI relationships;
b) examine how hybrid intelligence interaction can be designed to promote upskilling and avoid deskilling;
c) spark dialogue among the research disciplines of Human Computer Interaction (HCI), Computer Science, Information Systems (IS), Learning and Cognitive science, as well as policymakers and the private sector; and
d) provide arguments for redirecting the influence of AI technology on human workers, by shifting the focus from automation to augmentation.

2. DESKILLING, UPSKILLING AND RESKILLING IN THE AGE OF AI

Just as the industrial revolution shifted the role of human workers from individual craftsmanship to ensuring that machinery runs smoothly, the ability of today's AI to take on increasingly more complex tasks is shifting the role of knowledge workers. For example, Human-in-the-loop (HITL) (Bisen, 2020; Monarch, 2021) systems help plan, execute or evaluate a data acquisition task. In Human-on-the-loop (HOTL) scenarios, the human checks the final outcome (Nahavandi, 2017), and human-out-of-the-loop (HOOTL) does not include humans at all (Steelberg, 2019). Consider for a moment an AI designed for medical diagnostics. If the AI works alongside a human, but requires human interaction throughout the process, it is considered HITL. In cases where the AI conducts the diagnostic process on its own and only requires a yes or no from a human at the end, it is HOTL. If the AI completes the whole process without needing confirmation from a human, then it is considered HOOTL (Endsley & Kiris, 1995). Hybrid Intelligence is a subset of HITL, which pursues optimal synergies of the human and AI system (Akata et al., 2020; Dellermann et al., 2019).

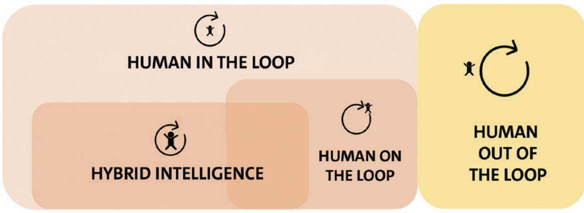

FIGURE 1: AN ILLUSTRATION OF DIFFERENT RELATIONSHIPS BETWEEN HUMAN AND MACHINE INTELLIGENT SYSTEMS.

One may rightfully argue for a more human-centric view and terminology, in which the human appears to be in control and the computer is "in or on the loop" (Shneiderman, 2020). Mackay (1999) provides an example of this in her discussion of developing computer systems to support the human-centric system of air traffic control. Here, the focus is on understanding human interaction in order to find ways of integrating systems that support it. From a human process perspective, systems can be understood from three major paradigms (Beaudouin-Lafon, 2004) -- computer-as-tool, computer-as-partner; and computer-as-medium. This human-centered design perspective for Hybrid Intelligence reveals tensions between paradigms for development that can affect whether AI systems lead to deskilling versus reskilling. In future work, we will provide a more granular specification scheme that also incorporates whether the human or the algorithm can be thought of as the primary driving factor. For now, however, we stick with the established computer-centric notation and specify that in the considerations introduced below, HITL should not be taken to imply that the computer is in control of the process, but rather that the human is more involved in the details of the task performance than is the case in HOTL.

A growing body of literature is devoted to deskilling in the age of AI (e.g., Brynjolfsson, & McAfee 2014; Sinagra, Rossi, and Raimondo, 2021; Sutton et al., 2018; Trösterer et al., 2016). This work has, however, focused primarily on concrete use cases and less on connecting these to a broader framework for the type of AI involved, such as the one we have introduced above. The main contribution of this work is to provide a strong call for developers to consciously consider which form of human-computer interaction is needed and to consider the unique risks of deskilling in each scenario.

A BASIS FOR HOW TO DEVELOP AI: KNOWLEDGE, SKILLS, AND THEIR EFFECTS ON WORK

Knowledge and work are intertwined, with work experience and organization affecting the ways in which employees build knowledge in changing and highly uncertain environments. In order to consider the significance of knowledge for framing an approach to deskilling, upskilling, and reskilling in the age of AI, we look at knowledge from two perspectives--first the nature of knowledge, and then types of knowledge.

THE NATURE OF KNOWLEDGE:

The nature of knowledge can frame our understanding of the connection between skills and work by examining definitions of knowledge in contrast to information that is generally stored in knowledge repositories. A key point relates to how knowledge is used in work. McDermott (1999) presented seminal considerations of the nature of knowledge and the importance of knowledge management in organizations. He articulated knowing as "a human act, whereas information is an object that can be filed, stored, and moved around. Knowledge is a product of thinking…" (p. 110) and the "…ability to use that information" (p. 105). Within AI, appropriately representing knowledge in a digital form was considered the primary challenge required to generate human-level intelligence for decades. However, this led to the application of rule-based approaches that resulted in an ever-growing prescriptive list without encoding insights. These AI systems were incapable of capturing human common sense both in physical (humans' natural understanding of the physical world) and social (humans' innate ability to reason about peoples' behavior and intentions) domains, and it remains an unsolved challenge to date (Marcus, 2020). This failure led to the most recent 'AI winter' that lasted until the advent of deep learning in the past half decade (Nicholson, 2018). Despite its success, we emphasize that deep learning systems do not represent knowledge in the sense defined above but only statistical inferences, and therefore it "thinks" much less like humans than may appear on the surface. It remains possible that the latest neuroscience insights into how humans use a nested series of reference frames in so-called cortical columns may lead to forms of AI more closely resembling human cognition (Hawkins, 2021). However, until then, we will have to design human-AI systems with highly asymmetric forms of cognition and modes of learning. We will return to this fundamental challenge below as we dive into the concept of Hybrid Intelligence, but first we return to the topic of technologically induced deskilling from a lens of types of knowledge.

TYPES OF KNOWLEDGE:

Many different frameworks exist to examine technologically induced changes in knowledge with respect to shifts in the types of knowledge required to accomplish the work and ways in which these types of knowledge are distributed between humans and technology (Arnold & Sutton, 1998; Barnard & Harrison, 1992, Venkatesh et al. 2003). To focus on types of professional and organizational knowledge such as procedural and domain knowledge, we consider five key factors. First, we have the task domain, which can range from motoric/craftsmanship (e.g. robotics) to the cognitive (e.g., decision making support, knowledge management systems) and the empathetic/caregiving (e.g., health technologies) domains. Second, we have the task characteristics, which Davenport and Kirby (2016) grouped as analyzing numbers, analyzing words and images, performing digital tasks and performing physical tasks. Third, we have associated work procedures which can be classified as skill-based behavior (automatic behavior in familiar situations, high efficiency), rule-based behavior (reasonably well known environment, medium efficiency) and knowledge-based behavior (novel/abnormal tasks, slow efficiency) following Bhardwaj's classification (2013). In general, procedural knowledge is expected to persist, whereas the importance of descriptive knowledge will decline (Trösterer, 2016). External effects range from replacing highly skilled workers with less skilled workers (restructuring the workforce) to causing deskilling at the individual level (degrading the overall proficiency level of the workforce) or eventual complete automation (diminishing the workforce) (Sutton et al., 2018). The numerous internal/personal effects include over-reliance on algorithms, decrease in professional involvement, dulling of professional decision-making skills and inability to make high-quality, unaided decisions (Mascha & Smedley, 2007; Sutton et al., 2018). Not surprisingly, in HITL cases where humans are merely the source of information to automate their job, this reduces the skills and expertise of human experts and might also create adoption barriers due to psychological resistance (Parente & Prescott, 1994; Pachidi et al. 2021) or a lack of trust and accountability (Dellermann, 2020).

CONSIDERATIONS FOR HOW TO MANAGE DESKILLING, UPSKILLING AND RESKILLING IN HUMAN-AI SYSTEMS

It is important to note that changes in workforce capabilities are not necessarily negative --- positive outcomes can be achieved if one deliberately plans and implements the technology with not only the particular human and algorithmic process in mind but also the synergistic interaction. In contrast to deskilling, upskilling occurs when workers build new, often broader and higher level skills which are beneficial to the workforce (Peng et al., 2018). Technology can facilitate upskilling in different ways including: (i) freeing up resources, so humans can use their expertise for further innovation, working on more cognitively demanding or rewarding tasks that computers cannot solve (Bresnahan et al., 2002) and (ii) introducing new demands and facilitating the acquisition of new skills that are necessary after the way of working has been transformed (Spenner, 1983). In the 21st century, the skills fostered by technological advancement are mainly high-level cognitive, analytical and less routine-cognitive and non-routine manual skills (Peng et al., 2018). Orellana (2015) suggested that deskilling and upskilling are not independent, but rather interact, resulting in reskilling, where decreased knowledge of a task is compensated by increased knowledge of the problem-solving system itself (Rinta-Kahila et al., 2018).

Below, we briefly review previous work on three well-studied areas of AI-implementation and skill changes—autonomous driving (Trösterer et al., 2016), finance (Mascha & Smedley, 2007), and medical diagnostics (Levy et al., 2019) — before introducing the Hybrid Intelligence framework as a means of further tapping into the potential of human-AI interaction.

EXAMPLES

AUTONOMOUS DRIVING

In traditional driving, a human controls the vehicle, often aided by advanced driver-assistance systems (e.g., cruise control), some of which are considered standard today, such as electronic stability control (ESC) and anti-lock braking systems (ABS). Driving this way requires a set of perceptual-motor and safety skills: navigation, planning, the ability to anticipate and dynamically adjust to the environment, knowledge of traffic rules, hazard perception and appropriate vehicle maneuvering (Trösterer et al., 2016). With increasing levels of automation (NHTSA, 2013), the driver can cede varying levels of vehicle operational control to technological systems (Cabitza et al., 2017). As a result, the skill levels needed to drive a car decrease, while at Level 4 automation, no human input is required (Coroamă & Pargman, 2020), since the human's role shifts from active engagement to mere monitoring (Sarter et al., 1997). This scenario raises the potential for loss of manual driving skills that can create highly dangerous situations, where the human driver is not paying attention and is suddenly asked to intervene at precisely the moment when the problem is too complex for the intelligent system (Dikmen & Burns, 2017; Zihsler et al., 2016).

FINANCE

In finance, accountants and auditors perform most of their tasks manually by going through large amounts of data to reach a conclusion (Mascha & Smedley, 2007). AI automates many of these mundane tasks by assisting in selecting information through automated data analysis and machine learning, while decision-support systems help sequence decision processes and provide decision recommendations, particularly for routine tasks. This can result in decreased domain-specific knowledge, as the main task of the user is narrowed down to judging the system's recommendations. The user essentially becomes an error-checker for the system. Other outcomes are declines in non-routine, or potentially routine decision-making skills (Mascha & Smedley, 2007), less knowledge acquisition (Noga & Arnold, 2002) and decreased levels of creativity (Wortmann et al., 2015).

MEDICINE

In medicine, new technology and deep learning are becoming more influential in fields such as ophthalmology (Levy et al., 2019), radiology (Hosny et al., 2018), molecular medicine (Altman, 1999) and pediatric care (Buoy Health, 2018). Without AI technologies, physicians determine a diagnosis and treatment plan based on physical examinations, relying on visual and manual perception and cognitive skills combined with professional skills (Hosny et al., 2018). As instances of automatic screening and decision-aid systems based on deep learning become more widespread, so do concerns that physicians will lose skills developed over months and years, and become prone to making decisions based solely on AI recommendations. Loss of clinical skills includes decreased ability to derive informed opinions on the basis of available data, increased stereotyping of patients, inaccuracy in identifying pathologies, decreased clinical knowledge and examination skills (or even failure to perform one) and decreased confidence in their own decisions (Levy et al., 2019). Issues of the role of management and the individual doctor's choices in the way they use the technology have been demonstrated to be key drivers of these risks (Hoff, 2011).

COUNTERACTING DESKILLING: THE INDIVIDUAL PERSPECTIVE

From the literature, we have identified three approaches to counteract the potential deskilling effects presented above. The first is education, which means identifying a set of fundamental skills of the field that should not be allowed to be deskilled and keeping them a part of teaching regardless of technological advancement (Levy et al., 2019). Examples include systems' technical driving skills for operating self-driving vehicles (Trösterer et al., 2016), thinking and analogical reasoning (Mascha & Smedley, 2007) in finance, and the ability to perform full physical examinations and identify pathologies in medicine (Levy et al., 2019). Second, professionals need to take an active role by relying on their own decisions first and foremost, only checking AI recommendations afterwards (Levy et al., 2019). Conceptual understanding of what algorithms are doing is also necessary on the human side (Sutton et al., 2018). Finally, the relationship between humans and AI needs to focus on collaboration rather than competition. This includes AI systems continuously providing explanations to users of their decisions for education (Mascha & Smedley, 2007), and determining the relative strength of humans and machines to design systems that effectively take advantage of both (Peng et al., 2018, Sutton et al., 2018). Additionally, the literature on cognitive load suggests that varying the level of feedback provided to decision-aid users might moderate the risks that result from under-reliance (Mascha & Smedley, 2007). Previous research on AI and human collaboration has emphasized that matching human and AI skills is critical (Mascha & Smedley, 2007), and that lack of learning on the human side can lead to lack of agency on the human side. A lack of mutual learning between humans and AI creates a performance gap in the potential outcome of such a sociotechnical system. Especially in uncertain, complex and dynamic environments that require constant updating of the knowledge about the world, it is crucial to empower humans to extend their knowledge and improve their skill set. To increase human levels of expertise, apart from updating their mental model of the world with new information, requires knowledge workers to also improve their meta-cognitive abilities, in order to better reflect on, and potentially act on the information provided to them by the machine during this collaboration. For example, in complex environments without access to ground truth or with highly time-delayed feedback, expert performance has been showed to correlate strongly with meta-cognitive abilities such as consistency and discrimination (Weis & Shanteau, 2003). If knowledge workers are not empowered to learn and improve, their input to the system can be systematically flawed, thus decreasing the ability of the overall system to improve.

One useful concept for approaching Hybrid Intelligence for human and machine learners is scaffolding (Quintana et al., 2004). Scaffolding can be conceptualized as a way to design AI systems that perform complex tasks (Collins, Brown & Newman, 1989). Scaffolding as a design lens can be applied to design human-AI interaction to accomplish business processes which change over time. Quintana et al. identify three ways in which scaffolding can occur: 1. by helping the learner make sense of, and attend to important parts or features of the task; 2. guiding learners throughout the process of solving the task; or 3. by prompting the learner to articulate and reflect on the task in-action.

Taking a scaffolding perspective on designing Hybrid Intelligent tools and processes provides a conceptual language for describing the ways in which humans and AI support each other while solving tasks more efficiently and more effectively.

COUNTERACTING DESKILLING: THE ORGANIZATIONAL PERSPECTIVE

Thus far, we have focused on AI-induced deskilling at the individual level in terms of concrete changes to the efficiency of the concrete task solution. A more general issue is, how to structure a technology innovation process within an organization in order to avoid detrimental side effects such as deskilling. This challenge has been studied for decades in the field of IS research and in the following section we will briefly review some organizational considerations arising from the introduction of AI-technologies in the workplace environment.

From an organizational perspective, deskilling can be seen as a sociotechnical phenomenon that encompasses organizational process, user choice and wider-level labor politics. Bhardwaj (2013) focuses on deskilling problems in terms of technology-organization-process interaction. He points out that explicitly routinizing expert knowledge through systems is a management strategy. He calls for counteracting deskilling through rethinking skills in the maritime industry with high levels of technology as related to three levels of ergonomics -- physical, cognitive and organizational design for management. To counteract deskilling for workers, training for these three levels is recommended. These strategies can counteract risks of deskilling seen in situations where automation proves detrimental through errors induced by improper use of technology. Thus, from an organizational perspective, counteracting deskilling can begin with a holistic undertanding of technology--organization--process interactions. Hoff (2011) shows that deskilling with technology can happen as a result of how users choose to interact with the system. In the field of medicine, he found that doctors' choices when working with systems that enabled more managerial control over their work led to deskilling outcomes. This finding underscores the managerial role in system design that offers potential for deskilling. Brugger and Gherke discuss economic frames for deskilling in the 18th, 19th and 20th centuries. One relevant frame casts deskilling in terms of managerial choices, where new technologies were introduced not to save money, but to reduce the bargaining power of skilled workers. In addition, they describe technology as bringing skill transformation, connecting it to shifts in the labour market with corresponding shifts in society.

3. THE CASE FOR HYBRID INTELLIGENCE

As evidence mounts that pure deep-learning systems will not, by themselves, deliver human-level intelligence for complex scenarios, researchers are increasingly turning to the problem of designing effective interactive human-AI systems (Hawkins, 2021; Heaven, 2019; Marcus, 2020). Many scholars refer to Hybrid Intelligence as the solution but define it loosely to encompass all of HITL-AI (Akata et al., 2020; Kamar, 2016; Lasecki, 2019; Prakash & Mathewson, 2020; Sinagra, Rossi & Raimondo, 2021), which greatly diminishes its value as a concrete, actionable design framework. Lyttinen et al., (2020) define the stronger concept of meta-human systems, which include both human and machine learning. They distinguish between trial-and-error and diffusion-based learning, and discuss both the implications for organizations and open challenges. Here, we follow Dellerman et al. 2019's related but somewhat more stringent three-step definition of Hybrid Intelligence: "the ability to achieve complex goals by combining human and artificial intelligence, thereby reaching superior results to those each of them could have accomplished separately, and continuously improve by learning from each other" (p. 640).

In this paradigm, Hybrid Intelligence systems combine human knowledge workers and AI agents to solve tasks that exceed the capabilities of either alone. The term "collectiveness" refers to situations in which human and AI agents collaborate towards a system-level goal, even if an individual agent's sub-goals differ from the overall system-level goal. The term "mutual learning" refers to the capacity of both knowledge workers and AI agents to improve their skills over time (Dellermann et al., 2019b).

Table 1 identifies the four types of human-AI partnerships shown in Figure 1 and illustrates the risks of deskilling as well as the potential for upskilling for each scenario. Hybrid Intelligence provides a comprehensive human-centered focus, and thus can be deliberately designed to maximize opportunities for upskilling, and minimizing the risk for deskilling; we will focus on this type of human-AI interaction for the rest of the paper.

Term	Definition	Example	Risks of deskilling	Potential for upskilling
Human in-the- loop (HITL)	*Humans provide data*			
	AI requires human interaction to solve the task	AI uses human-labeled data as the ground truth for training an object-detection system	Humans lose skills formerly acquired through direct experience and have less engaging jobs. Data quality may decrease over time and AI may learn "wrong" things	Humans continue learning and developing expertise, improving job satisfaction, while maximizing AI data quality
Human on-the- loop (HOTL)	*Humans check data*			
	AI conducts processes independently and only requires humans to check the final outcome	AI monitors and recommends missile defense and counter-strike measures that are then validated by humans	Humans become overly reliant on AI recommendations and can no longer adequately check the quality of AI results	Humans can focus on task understanding and retain agency when correcting for unintended outcomes
Human out-of- the-loop (HOOTL)	*No human involvement*			
	AI completes the entire task without human confirmation	AI handles algorithmic stock trading	Humans lose necessary monitoring skills and cannot correct for novel system failures or unintended consequences	Humans create value-added tasks that complement automated processes, reserving time and cognitive resources for strategic thinking and complex problem-solving
Hybrid Intelligence	*Humans and AI share agency*			
	Humans and AI each provide unique competence that together produce optimal results	Humans and AI share control of a visual search task	Humans lose a subset of skills that later turn out to be essential	Humans understand how to improve their performance on their own tasks and how to deliver input that allows AI algorithms to continually improve

Table 1: Overview of four common Human-AI relationships, including a brief definition, example, the risks of deskilling and the potential for upskilling human capabilities.

Like the field of Human-Computer Interaction, Hybrid Intelligence builds on sociotechnical systems theory. Sociotechnical systems theory describes how the social and technical systems need to work together, so system designers should consider how to appropriately coordinate human and AI skills, knowledge and talents in contrast to other methods that design the technical component first and only consider human needs later (Appelbaum, 1997). Hybrid Intelligence can thus be seen as a subcategory of sociotechnical systems with stricter requirements on the considerations of human learning and adaptation. Bednar and Welch (2020) explore sociotechnical system theory in so-called 'smart systems' which harness the Internet-of-Things, AI, and robotics used in organizations, finding that utilization of disruptive advanced technologies requires consideration from multiple perspectives taking into account the longer-term as well as the potential short term gain. Automation "at the expense of expertise seems a short-sighted solution" (Sutton et al., 2018, p.17) and can have unintended consequences in the long run. However, following established models of individual and organizational responses to change (Elrod & Tippett, 2002), upskilling mostly occurs with a conscious effort and often leads to initial productivity decreases. Those are then counteracted by substantial long-term gains to leverage the full potential of the technology. In contrast, Hybrid Intelligence can be used for many purposes at the organizational level, and whether upskilling is in focus depends on the organizational strategy and culture. Key points in leveraging Hybrid Intelligence for organizations include 1) configuring and coordinating human and AI roles in business processes; and 2) building short and long-term perspectives into the Hybrid Intelligence interaction design, particularly around designing work for upskilling in alignment with organizational strategy and culture.

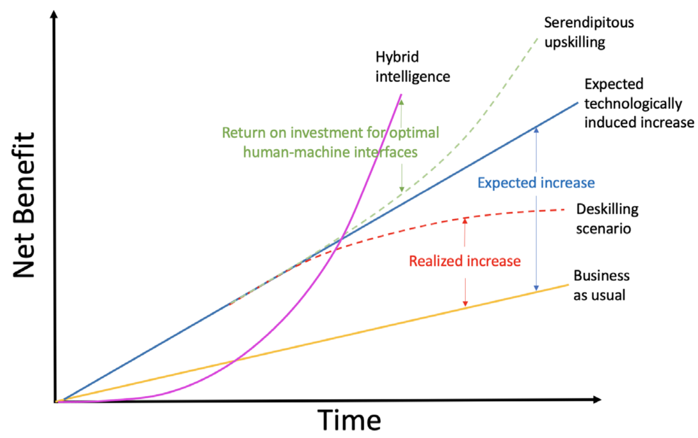

Figure 2: Conceptual, idealized map of digital change scenarios showing how a particular contextually relevant metrics (e.g., accumulated productivity) may increase over time under various scenarios for new AI-based technologies.
In this work, we hypothesize that investment in Hybrid Intelligence (systemic, holistic taking all stakeholders effects considerations in the design process) will pay off in the long run.

Figure 2 illustrates the temporal aspects of deskilling and upskilling from the point of view of a contextually relevant business metric (e.g. accumulated productivity). Here, we imagine that a new technology is introduced into a company and ideally provides a constant increase that leads to a linearly increasing accumulated metric. As the technology is embedded into the work culture, unexpected adverse effects may appear due to workforce deskilling. The case of the automated MCAS (Maneuvering Characteristics Augmentation System) system for the Boeing 737 Max illustrates the risk of inadequately designing for how less experienced users will interact with an intelligent system if it fails. Described as "an accident waiting to happen" (Christiansen, 2019), pilots' inability to wrest control over the aircraft when MCAS failed resulted in two deadly crashes. Boeing had decided to add overly heavy engines to the 737, originally designed in the 1960s, in order to compete with the newer Airbus design for the same market. Unfortunately, these engines made the aircraft unstable, which required engineers to design MCAS, which automatically adjusts the angle of the aircraft during takeoff. Boeing's management misrepresented the level of training required, since that would have required significant extra costs, and even hid its presence from pilots. MCAS engineers did not adequately consider the interaction between pilots, sensors, and the autopilot (Travis, 2019). and because of certain display elements, many pilots never had a chance to learn of its presence, much less how much it could change the angle of the aircraft (Christiansen, 2019). When it failed, pilots with extensive experience flying traditional 737s were able to compensate for the incorrect behavior of the MCAS system. However, younger pilots who had been trained primarily on flight simulators had no idea of what to do, and were unable to wrest back control and avoid crashing. This case shows both the dangers of deskilling, and the need for informing users as to the presence and role of an AI.

Creating true Hybrid Intelligence systems requires changes in how system designers create interactive systems and how managers introduce them into their organizations. For example, developers must consider both the immediate interaction between users and the AI system, as well as the long-term effects of that interaction. Managers must become more aware of how AI can affect both their employees and the use of their products through unintended consequences of Human/AI interaction. Taking a Hybrid Intelligence approach in the MCAS case would require reskilling pilots to ensure their awareness of how the autopilot works and their ability to disable it if necessary (Travis, 2019). This case demonstrates the complexity and nuances required of Hybrid Intelligence systems, where the design goes beyond the system in isolation to include design in real-world contexts, with humans working closely with AI systems. A key question then at the organizational level is: "What are the key barriers that hinder implementation of human-centered AI systems in organizational contexts?

THREE POSSIBLE REASONS COULD BE:

1. The highly publicized success of AI on well-contained tasks relative to human performance may lead to unrealistic expectations about the capabilities of off- the-shelf AI solutions.

2. Fully digital AI-solutions lend themselves to data-driven performance metrics. This may lead to an incremental series of algorithmic improvements, while understating the importance of human practices. Thus, short-term gains in productivity from algorithmic improvements or implementations may produce long-term deskilling and other unintended consequences.

3. Many corporate AI development projects are driven by a few highly technical experts, within or outside the organization, with esoteric knowledge of the inner workings of state-of-the-art AI. It is an imminent challenge within organizations to integrate these technical teams with parts of the organization having the training in psychology, user experience, organizational behavior or business development but do not possess a sufficiently deep understanding of AI to formulate their experience-based concerns or fully contribute with their competences. The design of such integrated Hybrid Intelligence systems is currently extremely new, with few well-documented cases to define best practices. Of these, many are limited to laboratory settings and have not been scaled to address the needs of industry.

We suggest that standardized frameworks for integrating IS systems at the organizational level such as the IT engagement model (Fonstad & Robertson, 2006) need to be revisited in the light of Hybrid Intelligence, to see whether IT governance, project management and linking mechanisms in the model can adequately account for the increasing technical complexity afforded by AI.

This type of investigation questions whether AI can be treated the same as other digitalization processes in business contexts. This also brings with it key discussions related to the human-centric viewpoint and its role in Hybrid Intelligence solutions. Using Hybrid Intelligence as a framework for human-AI interaction focuses on inspiring best practices for designing human-AI synergies and providing operational development criteria for creating value in organizations. Deskilling and upskilling consequences are a natural part of these considerations.

At both the individual and organizational level, a key task in developing and maintaining Hybrid Intelligence systems is to consider strong and natural support for the human's i) meta-cognitive skills ii) systems thinking (Bednar and Welch 2020, Sutton et al 2018) iii) complex problem solving (Dellermann et al., 2019), iv) creativity (Dellermann et al., 2019; Trunk et al., 2020; Wang et al., 2021), v) tacit knowledge (Basu et al., 2021), and vi) analogical reasoning (Sutton et al 2018). The first four are not domain-specific skills but rather complex, contextual and nuanced skills that are also highlighted as some of the most important skills for the 21st century (OECD, 2018; Soffel, 2016). The last two, tacit knowledge and analogical reasoning, contain some implicit domain knowledge, gained through experience, which is difficult to transfer from one person to another. Other skills will be important too, and further investigation into knowledge work skills that can be developed through Hybrid Intelligence systems should be a topic of study in the future.

At the society level, AI has engendered fear due to the history of deskilling and upskilling over the past 200 years, where technology and work have evolved together. With AI, the media has created the fear that humans may lose control of their systems, their skill sets, and their jobs through deskilling. However, we need to look at the organizational level to understand how and why AI is being incorporated into organizational strategies and business processes, and whether the deskilling risk is indeed one of replacement of human labor or simply change as usual. Key concepts on the society level relate to the shape of industries and the interaction between industries of production and those of experience. Future questions include 1) the issue of whether a 4-day work week might be needed to reshape how work and leisure is configured at the society level when Hybrid Intelligence systems become more widespread across organizations and industries; and 2) how institutions such as unions, educational systems and professional organizations will be affected by a widespread use of Hybrid Intelligence.

4. CONCLUSIONS AND RECOMMENDATIONS

In this paper, we set forth to provide an initial exploration of deskilling in the age of AI. Our work should be seen as a call for both further theoretical and empirical studies with interdisciplinary perspectives from cognitive science, management, computer science, philosophy and ethics as well as domain-specific case studies to substantiate those perspectives.

The risks and opportunities for deskilling in AI can be considered at individual, organizational and societal levels. To reflect on this, we first compared four different types of Human-AI interaction, HITL, HOTL, HOOTL and Hybrid Intelligence. We then provide examples of real-world human-AI collaborations, and best practices for addressing risks of deskilling and potentials for upskilling based on secondary sources. Next we focus on the Hybrid Intelligence category defined by Dellermann et al 2019 as "the ability to achieve complex goals by combining human and artificial intelligence, thereby reaching superior results to those each of them could have accomplished separately, and continuously improve by learning from each other" (p. 640). This definition provides both a design philosophy and actionable framework to develop and implement AI products so that human-centered issues such as deskilling are considered before there are long-term negative effects on individuals, organizations and society.

Hybrid Intelligence can be more challenging and time consuming in initial development in contrast to other more algorithmic AI oriented methods. However, we suggest that individuals will find an HI-solution easier to accept and adapt to as well as more supportive of skill growth. Organizations will find HI more effective in the long run and it will have the potential for positive societal effects such as job market growth. This is because Hybrid Intelligence focuses on collaboration between humans and AI, rather than competition and prioritizes mutual learning; thus it contributes practical solutions and organizational knowledge gains that reach beyond the capabilities of AI or humans alone.

We contribute to the field by reexamining the question of deskilling vs upskilling through the lens of four distinct forms of human-machine interaction (HITL, HOTL, HOOTL and HI) and by suggesting three key barriers for organizations moving to hybrid intelligence models. These are unrealistic expectations of capabilities of off the shelf solutions, prioritization of short term gains in productivity, and lack of teams which are knowledgeable of both the AI technology as well as psychology, user experience, organizational behavior or business development. However, the development of AI technologies, when approached from a Hybrid Intelligence framework also presents a rich opportunity. Hybrid Intelligence foregrounds human context and needs and encourages exploring new forms of interaction and synergies between humans and algorithms for reskilling and upskilling workers.

In conclusion, we believe that a Hybrid Intelligence framework offers managers and decision makers as well as all other stakeholders in the implementation ecosystem a valuable lens for creating inclusive human-AI integration processes and long-term beneficial business outcomes and bridging the short-term productivity focus in designing and implementing human-AI systems. The framework can provide guidance on how human and AI work can be configured within organizations for optimal use, based on key needs identified by the corporate strategy, education level and needs of the workers.

We conclude our essay by urging all stakeholders to consider two central questions:

> **1. What is the type of relationship between the human and the AI (HITL, HOTL, HOOTL or Hybrid Intelligence)?**
>
> **2. Are both human and machine systems learning continually throughout the process?**

We call for researchers and practitioners to combine case studies and theoretical considerations in the coming years to form a comprehensive framework for the synergetic human-machine interaction of the 21st century.

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