Dec 12th, 12:00 AM

What Are We Augmenting? A Multidisciplinary Analysis of AI-based Augmentation for the Future of Work.

Ines Baer
Vrije Universiteit Amsterdam, i.b.baer@vu.nl

Lauren Waardenburg
IESEG School of Management, l.waardenburg@ieseg.fr

Marleen Huysman
Vrije Universiteit Amsterdam, m.h.huysman@vu.nl

What Are We Augmenting? A Multidisciplinary Analysis of AI-based Augmentation for the Future of Work

Completed Research Paper

Inès Baer, Marleen Huysman
School of Business and Economics,
KIN Center for Digital Innovation,
Vrije Universiteit Amsterdam
1081 Amsterdam, Netherlands
i.b.baer@vu.nl
m.h.huysman@vu.nl

Lauren Waardenburg
IESEG School of Management
59000 Lille, France
l.waardenburg@ieseg.fr

Abstract

While augmentation is commonly presented as a desirable path in AI development and implementation, we have not yet found a shared definition for this concept. As the verb "to augment" needs to be followed by a target, we raise the question: What is augmented with AI? Building on a literature review of the augmentation narratives in five different disciplines – i.e., labor economics, computer science, philosophy, management, and information systems – we identify eleven distinct augmentation perspectives taken by scholars of those fields, including the underlying theoretical concepts that indicate what is intended to be augmented. This paper contributes to theory by "going beyond augmentation as collaboration" and helping us to move "towards collaboration for augmentation".

Keywords: Augmentation, artificial intelligence, human-AI interaction, multidisciplinary collaboration

Introduction

The increased prevalence of artificial intelligence (AI) – most commonly defined as technological systems capable of performing functions that would require intelligence if done by humans, such as learning, speech, planning and problem solving (Russell & Norvig, 2016) – is expected to change the world as we know it. For the coming decades, AI is expected to exceed human performance in many activities, including "translating languages (by 2024), writing high-school essays (by 2026), driving a truck (by 2027), working in retail (by 2031), writing a bestselling book (by 2049), and working as a surgeon (by 2053)" (Grace et al., 2018, p. 729). Compared to previous, not "intelligent", technologies, AI is particular in the sense that it is able to learn from data and generate rules, whereas the process to generate the results often remains opaque to even human experts, thereby reshaping work in unique ways (Faraj et al., 2018; Gal et al., 2020; Kellogg et al., 2020).

An initial reaction to the rise of AI was automation anxiety, or the fear of large-scale job-loss (Brynjolfsson & McAfee, 2014; Frey & Osborne, 2017). However, more recently, information systems (IS) and management scholars contrast this anxiety with a focus on *augmentation*, which includes opportunities to enrich human work (e.g., Raisch & Krakowski, 2020) and emphasizes the potential of human-machine interaction (e.g., Grønsund & Aanestad, 2020). Augmentation through human-machine interaction implies the need to bridge various domains such as the technical (i.e., computer science) domain of AI systems and the work domain of its users. This is because AI development and implementation itself is said to require multidisciplinary research (Dwivedi et al., 2019) and interdisciplinary collaboration (e.g., Lebovitz et al., 2022; Van den Broek et al., 2021). Consequently, this need for bridging disciplines, recently triggered scholars to call for more research that unpacks how different fields can come together (e.g., Bailey & Barley, 2020; Faraj & Pachidi, 2021).

However, while calls for research on the interdisciplinary nature of AI continue to grow, scholars have not yet questioned whether the underlying concepts used across disciplines are actually understood in the same way. Given the variety of disciplines that conduct research on AI and augmentation, it is very likely that the differences in language, methods, cultures and interests between the fields create barriers for communication and collaboration (Kusters et al., 2020). This leads us to wonder whether the various disciplines attach the same meaning to the concept of AI-based augmentation. While different disciplines refer to augmentation as a desirable path for AI that will ultimately benefit humans, the more fine-grained details behind this human-centric vision often remain unclear. In this paper, we therefore ask: *What is augmented with AI?*

Building on a literature review of publications from the disciplines of labor economics, computer science, philosophy, information systems, and management, we identify distinct augmentation perspectives taken by scholars residing in each field. In addition, we unpack each perspective in terms of what is intended to be augmented and identify the underlying theoretical concepts. This paper contributes to the ICIS community by providing conceptual clarity for the concept of augmentation, characterizing the intended outcomes of augmentation (i.e., what is augmented), going beyond understanding augmentation solely as (human-AI) collaboration. Additionally, our analysis highlights the differences and commonalities that exist between the disciplines in their theorizing of augmentation. We argue that this improved understanding provides an important basis for interdisciplinary knowledge sharing and to move towards multidisciplinary collaboration for augmentation, which can help us to get to a more encompassing understanding of how human-centric augmentation can eventually be achieved.

Introducing augmentation

The verb *to augment* is defined as a process of making something greater, more numerous, larger or more intense (Merriam Webster[1]). In the context of IT systems, the term *augmentation* was coined by computer scientist Douglas Engelbart in 1962 in relation to the emergence of the first universal computers. He described augmentation as follows:

> By 'augmenting human intellect' we mean increasing the capability of a man to approach a complex problem situation, to gain comprehension to suit his particular needs, and to derive solutions to problems. Increased capability in this respect is taken to mean a mixture of the following: more-rapid comprehension, better comprehension, the possibility of gaining a useful degree of comprehension in a situation that previously was too complex, speedier solutions, better solutions, and the possibility of finding solutions to problems that before seemed insoluble. (Engelbart, 1962, p. 1)

Since the introduction of augmentation as a concept in 1962, it has been used by scholars in a variety of fields and has recently gained renewed popularity with the increased attention to AI (Raisch & Krakowski, 2020). While scholars in a variety of disciplines (e.g., computer science, economics, philosophy) have used augmentation in relation to technology more generally (e.g., Autor, 2015; Bostrom, 2003; Skagestad, 1993), information system and management scholars have especially taken an interest in the phenomenon in relation to AI. They contrast augmentation most typically to (labor-replacing) *automation* (Raisch & Krakowski, 2020). In this view, automation is focused on replacement of work within its existing boundaries at a specific point in time, whereas augmentation enables new opportunities for development by "starting with what humans do today and figuring out how that work could be deepened rather than diminished by a greater use of machines" (Davenport & Kirby, 2015, p. 60).

Despite the popular use of the term augmentation, we fail to find a common definition. Augmentation is often broadly described as collaboration between humans and AI (Lebovitz et al., 2022). For example:

[1] https://www.merriam-webster.com/dictionary/augment#:~:text=Definition%20of%20augment&text=1%20%3A%20to%20make%20greater%2C%20more,job%20to%20augment%20her%20income

"Augmentation means that humans collaborate closely with machines to perform a task" (Raisch & Krakowski, 2020, p. 193); "In augmented intelligence methods, machines are taking actions and making decisions in collaboration with humans i.e., there is collaborative human-machine decision making" (Hassani et al., 2020, p. 143); "Human–ML augmentation, where humans and technology work together to perform organizational tasks jointly" (Teodorescu et al., 2021, p. 2). We argue however that this description of collaboration does not provide us with a valid definition for AI-enabled augmentation, as it focuses on the mechanism through which augmentation can be achieved but not on the intended outcome of augmentation, i.e., *what is augmented?* This question was the starting point of our literature review and will be the focus of this paper.

Method

The literature selection and analysis for this paper followed an explorative and iterative process (see Figure 1 for a complete overview of the steps taken). To get an understanding of how augmentation is described in the academic literature, we started with a search for articles on EBSCOhost Business Source Complete and on Google Scholar by using the terms "augmentation" or "augment" together with "artificial intelligence" or "technology" (later on adding "human" as a keyword). After a review of the abstracts of the resulting papers, we first selected the publications that explicitly referred to augmentation as well as AI or technology in their abstract. We then proceeded to read these papers diagonally and kept the papers that clearly used augmentation in their theorizing and provided a distinct description of the augmentation concept. This led us to a set of core papers that resided in five different disciplines, i.e., labor economics, computer science, philosophy, management and information systems. Using these core papers as our basis, we followed up on references and included additional papers, thereby continuously extending the reviewed material, also including practitioner-oriented papers, consulting reports, and management books.

For each of the publications in our database, we then extracted descriptive quotes that attached a meaning to the concept of augmentation; for example, "augmentation's potential to increase productivity, improve service quality, and foster innovation" (Raisch & Krakowski, 2020, p. 201). Based on the extracted quotations, we analyzed patterns, commonalities and nuances between the descriptions. We noticed that the perspective taken on augmentation varied between the different disciplines. We then categorized each publication according to the perspective(s) they were taking, e.g., labor augmentation, technology augmentation, human enhancement, cognitive extension, mutual symbiosis, hybrid intelligence. While there were some cases where a given augmentation perspective was taken in more than one discipline, our analysis showed that each perspective was clearly dominant in one of the five disciplines, and this is where we have included it. Some perspectives (even across disciplines) are closely related and appear very similar at first sight. However, our detailed analysis of the quotations highlighted the, sometimes slight but very important, nuances between those perspectives and justifies how we ended up with the eleven distinct augmentation perspectives.

Based on these emerging augmentation perspectives, we further expanded the literature search by searching for the keywords corresponding to those perspectives. For example, for "human enhancement", we used the keywords "super-human" and "post-human". This led us to include a few publications that do not explicitly use the term "augmentation" but that have had an important influence on how one of the augmentation perspectives is understood today (e.g., Ashby, 1956; Clark & Chalmers, 1998; Ihde, 1979; Licklider, 1960).

Ultimately, we included 65 publications in the augmentation literature review, including 18 from computer science, 12 from information systems, 8 from labor economics, 20 from management and 7 from philosophy. From these 65 publications across five disciplines, we identified eleven distinct augmentation perspectives, which are described in the following section.

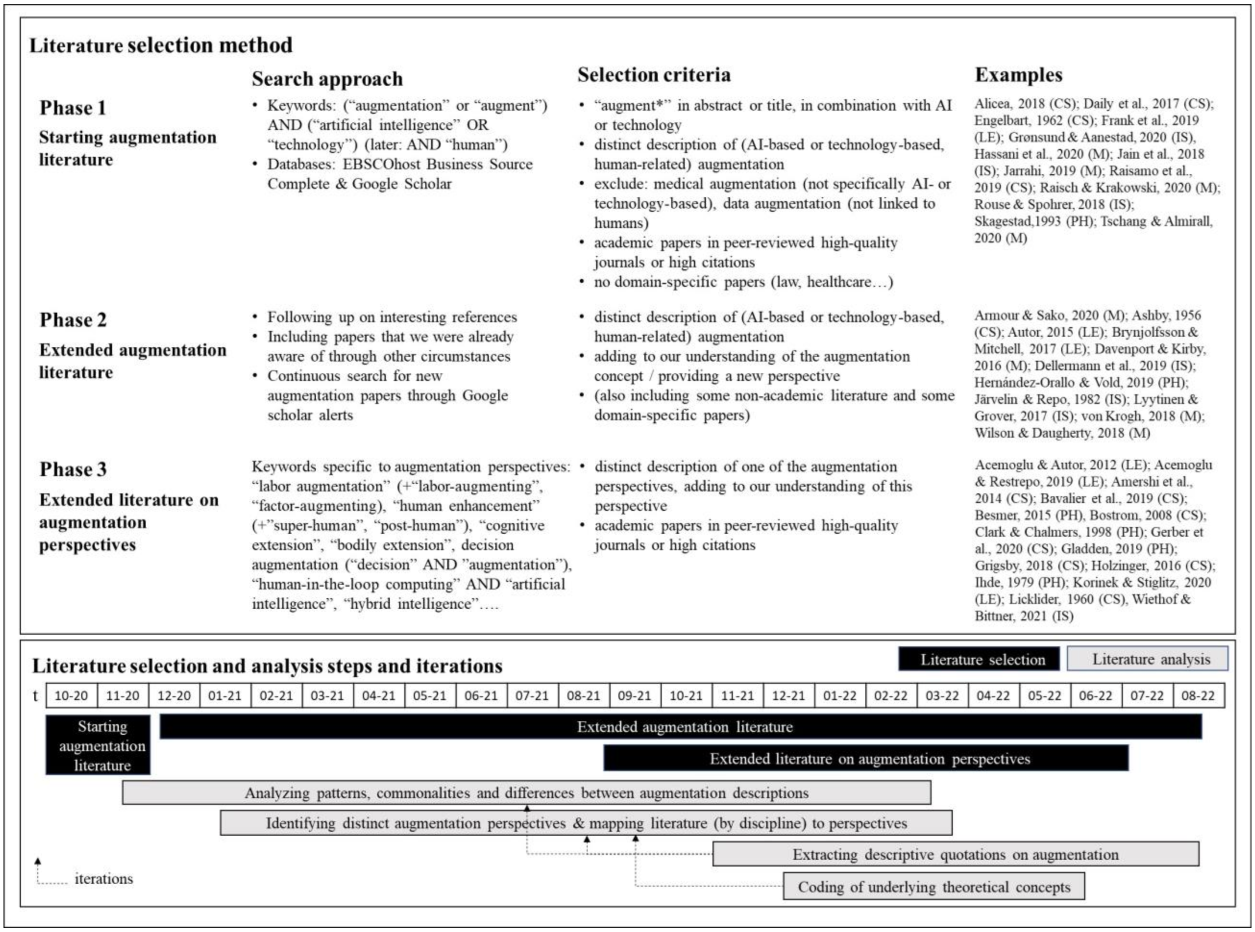

Figure 1. Process for literature selection and analysis

While the differentiation between augmentation perspectives already points to the fact that the five disciplines refer to the concept of augmentation in a different way, using different theoretical languages, it did not yet fully answer our initial question – i.e., *What is augmented with AI*? To provide answers to this question, we proceeded to identify the fine-grained theoretical concepts that were underlying the different augmentation perspectives. To do this, we open coded the augmentation quotes to identify the theoretical concepts used. After several rounds of refining the codes, we ended up with thirteen underlying concepts of what is intended to be augmented, listed in Table 1. If we take again our earlier quote, "augmentation's potential to increase productivity, improve service quality, and foster innovation" (Raisch & Krakowski, 2020, p. 201); in this example, we deduce that this perspective on augmentation intends to augment *productivity*, *business value* and *innovation*. Figure 2 summarizes the three different layers of analysis taken in this literature review – *Disciplines, Augmentation perspectives* and *Underlying theoretical concepts*.

Underlying theoretical concept	**Description**	**Number of publications focusing their augmentation perspective on this concept** (whereas most publications cover more than one concept)
Business value	Augmenting *business value* refers to being more effective, achieving better outcomes, better quality (for the customer, for the business…).	13

Cognitive capacity	Augmenting the *cognitive capacity* refers to enabling a superior cognitive processing performance – originating from the human, the machine, or a combined system.	11
Embodied characteristics	Augmenting *embodied characteristics* refers to enabling extended human embodied senses and action.	5
Employment	Augmenting *employment* refers to increasing the (human) labor share in the economy or increasing jobs.	7
Human mind	Augmenting the *human mind* refers to enabling superior human reasoning by using technological tools as an extension.	4
Human species	Augmenting the *human species* refers to significantly and lastingly enhancing the human condition and abilities beyond their natural form, leading eventually to super-humans.	10
Informed decision-making	Augmenting *informed decision-making* refers to generating new or improved insights that allow for better informed decisions.	15
Innovation	Augmenting *innovation* refers to doing something *new*: new business models, new tasks, new services…	9
Learned skills	Augmenting *learned skills* refers to humans increasingly applying and strengthening their skills and expertise, as a result of technological progress, or of humans learning from technology.	17
Problem-solving	Augmenting *problem-solving* refers to enabling society to solve complex problems in a new or improved way.	11
Productivity	Augmenting *productivity* (or efficiency) refers to doing the same thing faster, or doing the same with less input.	12
Task content & meaningfulness	Augmenting *task content & meaningfulness* refers to changing the nature of human tasks, in a positive way, e.g., more abstract tasks, more meaningful tasks, new tasks…	10
Technology performance	Augmenting *technology performance* refers to improving the AI's performance by having it learn from humans and the environment.	14

Table 1. List of the core theoretical concepts underlying augmentation (what is augmented)

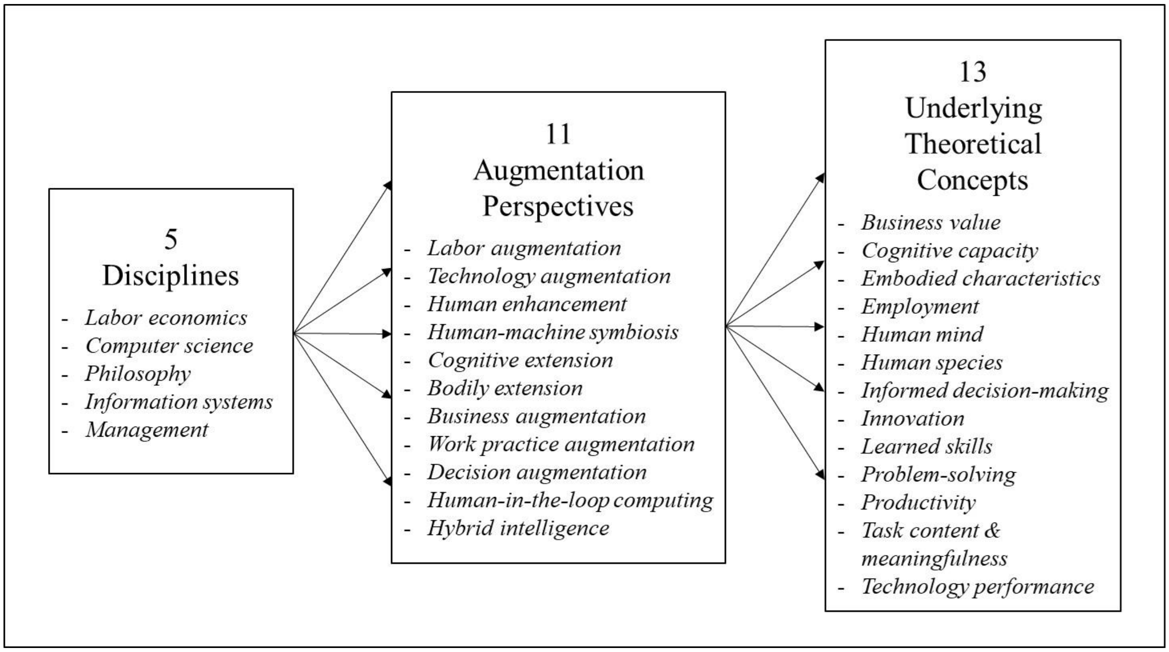

Figure 2. Layers of analysis for the augmentation literature review

Augmentation literature review

To answer the question "what is augmented?", in this section, we unpack the various augmentation perspectives and underlying theoretical concepts of the five core disciplines that discuss augmentation – i.e., labor economics, computer science, philosophy, information systems and management (see also Table 2). Below, we dive deeper into each of the disciplines and their respective augmentation narratives.

Discipline	**Augmentation perspective**	**Short description of the perspective**	**What is augmented? (underlying theoretical concepts)**
Labor economics	Labor augmentation	Labor augmentation occurs when AI complements (skilled) human labor and expands the demand for human labor in non-automated tasks.	Employment – via: productivity, innovation, task content, learned skills
Computer science	Technology augmentation	Technology augmentation occurs when AI is created as a superior (mostly autonomous) intelligence that can solve new complex problems. Humans might be kept "in the loop" as a means to enhance the technology's performance.	Problem-solving, technology performance
	Human enhancement	Human enhancement occurs when AI (lastingly and significantly) enhances the human body and/or mind beyond its natural state.	Human species
	Human-machine symbiosis	Human-machine symbiosis occurs when AI and humans are combined into a tightly coupled cognitive system with superior cognitive and problem-solving capacity.	Cognitive capacity, problem-solving
Philosophy	Cognitive extension	Cognitive extension occurs when humans use AI tools to (temporarily) outsource their reasoning and expand their cognitive capacity.	Human mind, cognitive capacity

	Bodily extension	Bodily extension occurs when humans use AI tools to (temporarily) outsource and expand their physical and sensory capacity.	Embodied characteristics
Information systems	Decision augmentation	Decision augmentation occurs when AI augments (organizational) information and decision-making with new insights.	Informed decision-making
	Human-in-the-loop computing (algorithm augmentation)	Human-in-the-loop computing occurs when AI performance and output is improved by humans acting as trainers, controllers/sustainers, explainers...	Technology performance
	Hybrid intelligence	Hybrid intelligence occurs when AI and humans are combined to augment each other / learn from each other (in organizational contexts).	Learned skills, technology performance
Management	Business augmentation	Business augmentation occurs when AI enables organizations to create superior business value, efficiency and innovation.	Business value, productivity, innovation
	Work practice augmentation	Work practice augmentation occurs when AI enables human workers to flourish, expand their expertise and take on more meaningful work.	Task content & meaningfulness, learned skills, informed decision-making

Table 2. Synthesis of the augmentation literature review per discipline

Labor economics

Scholars in the economics discipline, and in particular labor economics, have studied the dynamics between technologies and human labor for many decades (e.g., Goldin & Katz, 1998; Keynes, 1930; Simon, 1965). Studies in this area are typically interested in the macroeconomic effects of technological progress on human labor – i.e., substitution versus complementarity/augmentation – and in the key drivers of these effects (e.g., education level, nature of the task, etcetera). When it comes to augmentation, labor economics takes the perspective of *labor augmentation*: the increase in the demand for human labor and employment (Acemoglu & Restrepo, 2018b; Autor, 2015; Korinek & Stiglitz, 2021).

Studies in this field are based on an economic model where economic production output is created using different kinds of factors of production, mostly distinguishing between (human) labor inputs and (technological) capital inputs (Autor & Dorn, 2013; Autor et al., 2003). As such, technological progress can be *labor*-augmenting or *capital*-augmenting (Acemoglu & Restrepo, 2019; Korinek & Stiglitz, 2021). *Labor-augmenting* technological progress tends to create positive employment prospects for human workers. For example, intelligent navigation assistants allow more humans to work as drivers and are therefore considered as labor-augmenting (Korinek & Stiglitz, 2021). *Capital augmentation*, on the contrary, focuses on non-human resources in the economic production model, which includes machines, materials, software, etcetera. Technological progress can be capital-augmenting by raising the productivity of the technology itself (Korinek & Stiglitz, 2021). Capital augmentation allows firms to substitute capital for tasks previously performed by labor (Acemoglu & Restrepo, 2018a). For example, while navigation systems are labor-augmenting, self-driving cars can be considered capital-augmenting technological progress. This does not mean, however, that the demand for human labor decreases; it depends on the elasticity of the substitution between labor and capital (Acemoglu & Restrepo, 2018c). In fact, labor demand often increases as a result of capital augmentation (Acemoglu & Restrepo, 2018b).

To contrast substitution or displacement by technology, labor economics distinguishes between two different (labor) augmentation effects: the productivity effect and the reinstatement effect (Acemoglu & Autor, 2012; Acemoglu & Restrepo, 2018a, 2018b, 2019). The productivity effect implies that, by raising the productivity (and therewith usually the volume) of the automated tasks, there is also an incentive to increase the volume of other related, non-automated (labor-intensive) tasks (Autor, 2015). As such, technologies increase the value and relative employment of the labor performing those non-automated tasks (Bessen, 2016). While the productivity effect looks at labor share in existing tasks, the reinstatement effect looks at how technological progress may also enable the introduction of new tasks that emerge through innovation (Acemoglu & Restrepo, 2019). Whereas most technologies have historically been introduced to increase productivity (Murray et al., 2020), they can also lead to new product or service innovations (Calvino & Virgillito, 2018). The reinstatement effect is thus said to drive labor augmentation by generating new, labor-intensive, work content as a result of new innovations.

Labor economists are also interested in determining what type of human labor – i.e., in terms of task content and skills – is complemented or augmented by technology (Agrawal et al., 2019), although on a very macro level to allow for quantitative analysis. The main theories here are the "Skill-Biased Technological Change" (SBTC) and the "Routine-Biased Technological Change" (RBTC) theory. The SBTC theory looks at a uni-dimensional and highly simplified notion of skills (corresponding to education level) and argues that technological progress complements mostly high-skilled (i.e., high-educated) workers (Acemoglu & Autor, 2012). The RBTC theory goes beyond this uni-dimensional view of education level towards a multi-dimensional view of task categorization. It categorizes tasks into routine vs. abstract and manual vs. cognitive (analytical or interactive), where some (routine) human tasks are substituted by information technology, while other (abstract) tasks are complemented by the same technology (Autor et al., 2003).

In sum, the labor economics discipline takes one primary perspective on augmentation: the labor augmentation perspective, which is primarily focused on augmenting *employment*. This is further unpacked in terms of augmenting *productivity*, *innovation*, *task content*, and *skills*.

Computer science

The computer science discipline also has a distinct interest in augmentation. Augmentation perspectives in computer science range from technology-centric, i.e., *technology augmentation* or *human-in-the-loop computing* (e.g., Ashby, 1956; Holzinger, 2016) to human-centric, i.e., *human enhancement* (e.g., Bostrom, 2008; Daily et al., 2017; Raisamo et al., 2019), with many scholars working towards a *symbiosis* between humans and technology (e.g., Gerber et al., 2020; Grigsby, 2018; Licklider, 1960).

Scholars taking a *technology augmentation* perspective argue that humans have significant cognitive limitations that would be beneficial to overcome. They express a vision of creating superior artificial intelligence that is able to autonomously solve societal problems (e.g., Ashby, 1956; Skinner et al., 2014). In this perspective, augmentation is targeted at the technology itself, and at the ability to solve complex problems. The human is either disregarded or kept "in-the-loop" as a means to enhance the technology's performance. We therefore understand human-in-the-loop computing as a form of technology augmentation. This is illustrated by Holzinger (2016, p. 119) who describes human-in-the-loop computing as "algorithms that can interact with agents and can optimize their learning behavior through these interactions, where the agents can *also* be human". Examples of technology-centric augmentations are AGI (artificial general intelligence) projects such as DeepMind and OpenAI (Fitzgerald et al., 2020).

There are also scholars in the computer science community that take a more human-centric approach[2], aiming to use the potential of technology to create a new species of "humans 2.0" (Raisamo et al., 2019) or "posthumans" (Bostrom, 2009), "greatly exceeding the maximum attainable by any current human being without recourse to new technological means" (Bostrom, 2008, p. 56). This perspective is most often referred to as *human enhancement*. Scholars taking this perspective consider how technological devices (and even medical substances) can be integrated with the human body in order to improve or restore the human body and mind (Daily et al., 2017; Raisamo et al., 2019), thereby enhancing human abilities such as cognitive, sensory, emotional and physical abilities beyond their natural state (Alicea, 2018; Bavalier et al., 2019; Bostrom, 2008; Xia & Maes, 2013). Augmentation, in this case, should be significant and usually lasting, truly altering the human species, and even aiming as far as immortality (Bostrom, 2003, 2008). The technology considered here is mostly invasive, being integrated into the human body (such as chips) or

[2] Although it might be questioned if the vision is really human-centric if it goes against what most humans would wish for their future: https://www.pewresearch.org/science/2016/07/26/u-s-public-wary-of-biomedical-technologies-to-enhance-human-abilities/

tightly linked with the human body (such as prostheses or augmented reality glasses) (Bavalier et al., 2019; Daily et al., 2017; Raisamo et al., 2019).

Finally, the *human-machine symbiosis* perspective describes a vision for a complementary (symbiotic) relationship between human and artificial intelligence (e.g., Licklider, 1960). Scholars taking a human-machine symbiosis perspective regard humans and machines as more or less equal partners that are tightly coupled into a so-called cognitive unit or system (Gerber et al., 2020). This combined unit is considered as a thinking entity in its own right (e.g., "the resulting partnership will think" (Licklider, 1960, p. 4)). The primary aim is to optimize this combined system (and not the human or technology individually) to augment its cognitive and problem-solving capacity (Gerber et al., 2020; Grigsby, 2018; Licklider, 1960). To achieve this symbiotic relationship, the cognitive system needs to be designed in a closed information loop where both sides must learn to understand each other and "seamlessly" or even "intuitively" react to each other "in real time" (Grigsby, 2018; Licklider, 1960; Skinner et al., 2014). The result is that humans and machines become co-dependent over time (Gerber et al., 2020). Human-machine symbiosis remains mostly in the realm of the future. Current examples moving in this direction are augmented reality devices building on brain-computer interfaces.[3]

In sum, the computer science discipline takes three distinct perspectives on augmentation: technology augmentation, human enhancement and human-machine symbiosis. The technology augmentation perspective focuses on augmenting *problem-solving* and *technology performance*, the human enhancement perspective on augmenting *the human species*, and the human-machine symbiosis perspective on augmenting *cognitive capacity* and *problem-solving*.

Philosophy

A third community that engages in perspectives around augmentation resides in the field of philosophy. Here, scholars mainly focus on two augmentation perspectives: *cognitive extension* and *bodily extension*.

The *cognitive extension* thesis was popularized by Clark and Chalmers (1998), who state that artifacts in a person's environment can serve as extensions of their cognitive state beyond the biological organism, thus not limiting the mind to what happens inside our brains (Clark & Chalmers, 1998). According to this perspective, humans can outsource some cognitive functions to "cognitive extenders" that are external to the human body (Hernández-Orallo & Vold, 2019), and thereby reach a superior reasoning and cognitive capacity. The emphasis here is that technologies serving as cognitive extenders are considered as *tools*, to be used by humans, and not as autonomous systems or partners of humans (as we have seen in the computer science literature) (Hernández-Orallo & Vold, 2019; Skagestad, 1993). Early examples of cognitive extenders are pen and paper, as an extension of memory (Clark & Chalmers, 1998), or the abacus as an extension for mathematical problem-solving (Farrow, 2017). More recent (technological) extenders are personal computers, mobile phones and of course AI-based applications (Hernández-Orallo & Vold, 2019; Skagestad, 1993). Cognitive extension is a *temporary* effect occurring only while using the cognitive extender, and that is lost when the tool is not used, thus not leading to a lasting human enhancement.

Beyond cognitive extension, philosophers also emphasize the role of technological progress in augmenting the body, via *bodily extension* (Besmer, 2015; Hernández-Orallo & Vold, 2019; Ihde, 1979). This includes the extension of purely physical functions (e.g., manipulation, strength) but also sensory functions, such as visual processing and auditory processing (Besmer, 2015). A common example of bodily extension is the blind man's stick that becomes an extension of his arm or even his vision (Merleau-Ponty, 1945). Another example is robotic surgery, where robotic arms, controlled by human surgeons, extend the fine motor skills of the surgeon's arms and hands (Sergeeva et al., 2020). This bodily extension might lead to amplification (or augmentation) of some bodily characteristics but also tends to reduce others (Ihde, 1979; Kiran, 2015); for example, surgeons might gain in fine motor skills but lose the feeling of touch of the tissue (Sergeeva et al., 2020). In the bodily extension perspective, a further difference is made between extension and incorporation. Contrary to extension, an incorporation means that the human has integrated the technology into their own body schema (Besmer, 2015). If we take again the example of robotic surgery: if surgeons are temporarily using robotic arms to perform their surgery, this is considered a bodily extension but not an incorporation. The surgeon does not feel body ownership of the robotic arms (De Preester, 2011). If the surgeon would however use technological prosthesis attached to his or her body or even integrated in the

[3] https://www.frontiersin.org/articles/10.3389/fnhum.2020.00144/full

body, which would lead to a renewed body schema or feeling of body ownership, then it could be considered as enhancement rather than extension.

In sum, the philosophy discipline distinguishes between cognitive extension and bodily extension. Whereas the cognitive extension perspective focuses on augmenting the *human mind* and *cognitive capacity*, the bodily extension targets augmenting the *embodied characteristics*.

Information systems

Information systems scholars are in one of the disciplines that engaged more recently with the augmentation concept, mainly driven by the increasing interest in AI and its consequences (e.g., Dellermann et al., 2019; Rouse & Spohrer, 2018; Teodorescu et al., 2021). From this literature, three different augmentation perspectives emerge: *decision augmentation*, *human-in-the-loop computing / algorithm augmentation* (similar to the perspective in the computer science discipline), and *hybrid intelligence*.

In the *decision augmentation* perspective, the primary focus is on augmenting the *information* that can be used for better organizational decision-making (e.g., "humans and algorithms are configured to transform data into value-added output" (Grønsund & Aanestad, 2020, p. 3)). AI is able to learn from historic data and generate insights that are new or presented in a different way (Wilson & Bataller, 2015). These machine-generated insights can help organizations improve their understanding of a particular situation (Järvelin & Repo, 1981). This perspective is also concerned with how humans use these new insights, integrate them in their decisions and create value for the organization (Grønsund & Aanestad, 2020; Lyytinen & Grover, 2017). This goes beyond individual decision-making, looking at organizational processes and decision models (Lyytinen & Grover, 2017). Augmented hiring decisions (Van den Broek et al., 2021) and augmented loan decisions (Luong et al., 2019) are common examples of decision augmentation.

Human-in-the-loop computing is primarily a technology-centric perspective with a particular focus on augmenting the performance of machine learning algorithms, also referred to as "augmenting the algorithm" (Grønsund & Aanestad, 2020). The main aim in the perspective is the advancement of the technology, but not necessarily with the objective of creating completely autonomous systems. The human-in-the-loop dimension is a central element, where augmentation is specifically distinguished from automation by the fact that humans remain involved (e.g., "insights are produced with expert involvement (augmentation) or without it (automation)" (Van den Broek et al., 2021, p. 1575)). The key emphasis in this perspective (in contrast to the technology augmentation perspective in computer science) is the variety of active roles that humans need to take to augment AI, e.g., actively training the learning algorithm, sustaining it, supervising and controlling its output, and explaining the results to others (e.g., Teodorescu et al., 2021; Wilson & Daugherty, 2018); such tasks are referred to as "augmentation work" (Grønsund & Aanestad, 2020).

On the other hand, the *hybrid intelligence* perspective defines augmentation as combining the strengths of human and artificial intelligence to achieve superior results and to allow both to continuously improve by learning from each other (Dellermann et al., 2019). It appears that this is similar to the human-machine symbiosis perspective introduced in the computer science section (in the sense that it considers humans and technology as real partners). However, the symbiosis perspective looks at the partnership from a cognitive standpoint, as a combined cognitive unit, while the hybrid intelligence perspective considers human and artificial intelligence more from an organizational standpoint, as distinct team members with different roles in the organization – e.g., the AI diagnosing cancer and the radiologist explaining the results to the patient (Rouse & Spohrer, 2018). The hybrid intelligence perspective thus focuses primarily on how combined human-machine systems enable humans and machines to co-evolve, learn from each other and augment each other's "expertise" (e.g., Dellermann et al., 2019; Rai et al., 2019). In other words, the perspective centers around learning loops between human and artificial intelligence, where AI learns from humans via interactions and datasets, and humans learn from AI because it generates new insights and presents them in a distinct way (e.g., Benbya et al., 2020; Rouse & Spohrer, 2018). An example here would be radiologists using a cancer diagnosis tool that learns from the radiologists' feedback, while at the same time the radiologists learn from the output of the tool which helps them become better medical professionals (Kim et al., 2021).

In sum, the IS discipline focuses on three distinct perspectives: decision augmentation, human-in-the-loop computing and hybrid intelligence. Decision augmentation augments *informed decision-making*, human-in-the-loop computing focuses on augmenting *technology performance*, whereas hybrid intelligence enables the mutual augmentation of both the artificial intelligence (*technology performance*) and human intelligence (*learned skills*).

Management

With growing management interest in AI, the concept of augmentation has become popular in recent years among management scholars, especially in the fields of organization science and (digital) strategy. This perspective mainly functions as a contrasting, more positive narrative to the one emphasizing labor-replacing automation anxiety (Raisch & Krakowski, 2020). In this literature, we are able to see two main perspectives emerging: *business augmentation* and *work practice augmentation*.

The *business augmentation* perspective, driven primarily by strategy scholars, focuses on augmenting business value or performance (Allen & Choudhury, 2021). Superior business value can be achieved by augmenting the productivity/efficiency or the effectiveness/quality of existing business processes (e.g., Raisch & Krakowski, 2020; Ryder, 2017; Sampson, 2020; Wilson & Bataller, 2015). It can also be achieved by augmented innovation – for example, of products (e.g., new drug discovery enabled by AI), services (e.g., prediction services), business models (e.g., platform models based on smart matching). Both humans and AI can be considered as creators of business value, and scholars taking the business augmentation perspective typically compare “algorithm-augmented to self-performance” (Allen & Choudhury, 2021, p. 8).

The *work practice augmentation* perspective, driven by organization science scholars, focuses on augmentation of tasks, skills, and the practice of decision-making in a work context. The perspective is human-centric; considering it important to keep humans in a superior position, and technology as tools to be used by humans (e.g., Hassani et al., 2020; Von Krogh, 2018). While philosophers focus on the individual, mostly independent of his environment, the work practice community looks at the organizational context and on human work in practice, while the work is being performed (Waardenburg et al., 2021). Scholars (and practitioners) taking this perspective emphasize that technological progress should allow humans to take on more meaningful and valuable tasks, as AI may take care of routine work (e.g., Davenport & Kirby, 2016; Plastino & Purdy, 2018; Raj & Seamans, 2019), or work that was previously not possible and that is newly enabled by AI’s potential (Davenport & Kirby, 2015; Sampson, 2020). They also note that augmentation is about human workers building on their unique strengths (complementary to AI) and expand their expertise by learning from the insights generated by AI (e.g., Davenport & Kirby, 2016; Lebovitz et al., 2022; Tschang & Almirall, 2021). In addition, they focus on how human workers can engage with the technology, to critically judge its output and integrate it into their own decision-making, neither blindly accepting nor blindly refusing it (e.g., Burton et al., 2020; Lebovitz et al., 2022; Waardenburg et al., 2022).

In sum, scholars in the management discipline distinguish between business augmentation and work practice augmentation. It appears that the business augmentation perspective focuses on augmenting *business value* (effectiveness), *productivity* (efficiency) and *innovation*, while work practice augmentation targets the augmentation of *task content & meaningfulness*, *learned skills* and *informed decision-making*.

Discussion

To unpack the concept of augmentation and to better understand what AI-driven augmentation will look like in practice, we asked: *What is augmented with AI?* The identification of these distinct categories of what is being augmented in the different disciplines has consequences for the popular understanding of augmentation as a “collaborative endeavor” (e.g., Akata et al., 2020). More specifically, our insights offer contributions to the conceptual understanding of augmentation and what this means for how augmentation can be achieved.

Beyond augmentation as collaboration

A core insight from our study is that augmentation, as of yet, is still ill-defined, and most often referred to as “humans and AI collaborating” (e.g., Hassani et al., 2020; Lebovitz et al., 2022; Raisch & Krakowski, 2020; Teodorescu et al., 2021). We argue that, while this collaboration-focused definition describes the mechanisms of *how* augmentation should be achieved, the intended outcome – or *what* is being augmented – is commonly left out. It can be expected that conceptual confusion regarding what actually will be augmented, will hinder further attempts to achieve augmentation. To reach greater conceptual clarity regarding augmentation, we unpacked the underlying theoretical concepts of AI-based augmentation that provide a more fine-grained and nuanced perspective on what is being augmented, ranging from technology performance to human skills, from problem-solving to employment, and from productivity to cognitive capacity. We emphasize that these underlying concepts allow us to go *beyond understanding augmentation as collaboration* to develop a common explanation per discipline.

With our analysis, we point out that each discipline has a distinct understanding of augmentation that is driven by, for example, the commonly used level of analysis (e.g., labor economics is driven by large-scale macro-level research). These differences in meaning given to augmentation in the various disciplines have so far remained largely hidden from scholars engaging with this concept. This is problematic since hidden differences can lead to confusion when collaboration between disciplines is required or preferred.

Towards collaboration for augmentation

While each discipline has their own answer to what is being augmented, in general, they all strive for augmentation to benefit humans; be it, for example, by enhancing or extending human abilities through AI, by developing autonomous AI capable of solving complex societal (and therefore human) problems, by creating economic value and demand for human employment, or by making human work practices more meaningful. The overarching focus on the human also means that the perspectives we identified can complement each other to arrive at a more encompassing and fine-grained understanding of human-centric augmentation, which scholars urgently call for (Raisch & Krakowski, 2020; Teodorescu et al., 2021).

Such a more holistic theorizing of augmentation requires knowledge sharing between the different disciplines. However, existing research on knowledge sharing between fields or communities already pointed at the need for a common language – or at least a shared understanding of the core concepts – to successfully transfer knowledge from one discipline to the next (e.g., Brown & Duguid, 1998; Carlile, 2004). The lack thereof is exactly the issue with augmentation that we point out in this paper. To build a shared understanding, our study offers a first step by providing conceptual clarity on augmentation per discipline.

Beyond sharing knowledge and creating a shared understanding, a point can be made about the need for interdisciplinary collaboration on AI-based augmentation. AI as a field is already today considered to require multidisciplinary perspectives to harness all the potential that the technology has to offer while at the same time preventing adverse effects (e.g., Akata et al., 2020; Bailey & Barley, 2020; Dwivedi et al., 2019; Kusters et al., 2020). With this paper, we argue that this same need for interdisciplinary collaboration applies to research on augmentation. Such collaborations can lead to synergies and mutual benefits between the fields (Kusters et al., 2020). To pursue human-centric, AI-based augmentation, organization scholars can take inspiration and benefit from the insights of other fields; and the same is true the other way around. Pursuing such an objective will require different fields with distinct professional languages to agree on, and collectively work towards a shared goal (Bailey & Barley, 2020). With our in-depth analysis of the meaning of augmentation across disciplines, we offer the first steps for developing a shared understanding (that can lead to shared goals) between these disciplines, thereby providing an important basis for moving *towards interdisciplinary collaboration for augmentation*.

Limitations and future directions

It is worth noting several boundary conditions of our study, which also open up opportunities for future research. For analytical clarity, which becomes even more important when performing a literature review that crosses disciplinary boundaries, we decided to only include papers that specifically referred to, and theorized, augmentation (or one of the identified augmentation perspectives). While we are convinced that we obtained a thorough understanding of the various perspectives on augmentation residing in each discipline, some works might have been left out of the review when the authors used a term other than augmentation to describe the same phenomenon. This also re-emphasizes the need for conceptual consistency, especially when the concept itself is used in multiple disciplines.

Also, our paper shows that scrutinizing different disciplines to understand what is being perceived as augmentation will help us to develop a common understanding of what is being augmented. However, as we focused our paper on existing perspectives on augmentation, it emerged that all fields maintain a more traditional human-machine dichotomy. While we limited our analysis to the existing works, future research could build on the sociomateriality literature (e.g., Cecez-Kecmanovic et al., 2014; Orlikowski & Scott, 2008; Østerlund et al., 2020) to go beyond the distinction between humans and machines to ask how such entanglements or apparatuses are augmented. This question is particularly relevant to IS scholars taking a hybrid intelligence perspective, as well as to management scholars taking a work practice augmentation perspective.

In addition, in this study we mainly aimed to unpack the distinct perspectives on augmentation residing in the five core disciplines and pointed at the need to learn from each other to move towards interdisciplinary collaboration for augmentation. Yet, in this paper we did not unpack how scholars in different disciplines can learn from each other, nor how interdisciplinary collaboration for AI-based augmentation happens in practice. We encourage future research to unpack the research questions that might emerge, as well as the empirical processes that develop when the different disciplines come together to develop a shared understanding of AI-based augmentation.

Finally, while in this study we focused on AI as an umbrella term for multiple emerging technologies, we agree with recent works that push for a more nuanced perspective, including the specifics of the technology under consideration (e.g., Huysman, 2020; Van den Broek et at., 2021; Waardenburg et al., 2022). As research on AI-based augmentation continues to advance, we encourage future research to open up the technology by being more specific about, e.g., the algorithms used, and to unpack their potentially different consequences for AI-based augmentation.

Conclusion

The differences in meaning given to augmentation between the various disciplines working on or with this concept have so far remained largely hidden from view, which can be problematic when sharing knowledge. This study offers a first step to facilitate knowledge sharing in the further development and implementation of AI by providing conceptual clarity on augmentation per discipline. Highlighting commonalities and differences between the disciplines of labor economics, computer science, philosophy, information systems, and management will allow scholars as well as practitioners to move towards multidisciplinary collaboration to advance the research, development, and implementation of AI-based augmentation.

References

Acemoglu, D., & Autor, D. (2012). What does human capital do? A review of Goldin and Katz's The race between education and technology. *Journal of Economic Literature*, 50(2), 426–463. https://www.aeaweb.org/articles?id=10.1257/jel.50.2.426

Acemoglu, D., & Restrepo, P. (2018a). The race between machine and man: Implications of technology for growth, factor shares and employment. *American Economic Review*, 108(6), 1488–1542. https://doi.org/10.1257/aer.20160696

Acemoglu, D., & Restrepo, P. (2018b). Artificial intelligence, automation and work. *NBER Working Papers*, 24196, 1–41. https://doi.org/10.3386/w24196

Acemoglu, D., & Restrepo, P. (2018c). Modeling automation. *AEA Papers and Proceedings*, 108, 48–53. https://doi.org/10.1257/pandp.20181020

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Agrawal, A., Gans, J., & Goldfarb, A. (2019). Exploring the impact of artificial intelligence: Prediction versus judgment. *Information Economics and Policy*, 47(C), 1–6. https://doi.org/10.1016/j.infoecopol.2019.05.001

Akata, Z., Balliet, D., de Rijke, M., Dignum, F., Dignum, V., Eiben, G., Fokkens, A., Grossi, D., Hindriks, K., Hoos, H., Hung, H., Jonker, C., Monz, C., Neerincx, M., Oliehoek, F., Prakken, H., Schlobach, S., van der Gaag, L., van Harmelen, F., ... Welling, M. (2020). A research agenda for hybrid intelligence: Augmenting human intellect with collaborative, adaptive, responsible, and explainable artificial intelligence. *Computer*, 53(8), 18–28. https://doi.org/10.1109/MC.2020.2996587

Alicea, B. (2018). An integrative introduction to human augmentation science. *arXiv,* 1804.1052, 1–23. https://doi.org/10.48550/arXiv.1804.10521

Allen, R., & Choudhury, P. (2021). Algorithm-augmented work and domain experience: The countervailing forces of ability and aversion. *Organization Science*, 33(1), 149–169. https://doi.org/10.1287/orsc.2021.1554

Ashby, W. (1956). Design for an intelligence-amplifier. In C. Shannon, & J. McCarthy (Eds.), *Automata studies* (pp. 215–234), Princeton University Press.

Autor, D. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, 29(3), 3–30. https://doi.org/10.1257/jep.29.3.3

Autor, D., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, 103(5), 1553–1597. https://doi.org/10.1257/aer.103.5.1553

Autor, D., Levy, F., & Murnane, R. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, 118(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Bailey, D., & Barley, S. (2020). Beyond design and use: How scholars should study intelligent technologies. *Information and Organization*, 30(2), 1–12. https://doi.org/10.1016/j.infoandorg.2019.100286

Bavalier, D., Savulescu, J., Fried, L., Friedmann, T., Lathan, C., Schürle, S., & Beard, J. (2019). Rethinking human enhancement as collective welfarism. *Natural Human Behaviour*, 3(3), 204–206. https://doi.org/10.1038/s41562-019-0545-2

Benbya, H., Pachidi, S., & Jarvenpaa, S. (2021). Special issue editorial: Artificial intelligence in organizations: Implications for information systems research. *Journal of the Association for Information Systems*, 22(2), 281–303. https://doi.org/10.17705/1jais.00662

Besmer, K. (2015). What robotic re-embodiment reveals about virtual re-embodiment. In R. Rosenberger, & P. Verbeek, (Eds.), *Postphenomenological investigations: Essays on human–technology relations* (pp. 55–72). Lexington Books.

Bessen, J. (2016). How computer automation affects occupations: Technology, jobs, and skills. *Boston University School of Law Research Paper*, 15-49, 1–45. https://doi.org/10.2139/ssrn.2690435

Bostrom, N. (2003). Human genetic enhancements: A transhumanist perspective. *Journal of Value Inquiry*, 37(4), 493–506. https://doi.org/10.1023/b:inqu.0000019037.67783.d5

Bostrom, N. (2008). Why I want to be a posthuman when I grow up. In B. Gordijn, & r. Chadwick (Eds.), *Medical enhancement and posthumanity* (pp. 107–136), Springer Netherlands.

Bostrom, N. (2009). The future of humanity. In J-K. Berg Olsen, E. Selinger, & S. Riis Aldershot (Eds.), *New waves in philosophy of technology* (pp. 186-216), Palgrave Macmillan.

Brown, J., & Duguid, P. (1998). Organizing knowledge. *California Management Review*, 40(3), 90–111. https://doi.org/10.2307/41165945

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W.W. Norton & Co.

Burton, J., Stein, M-K., & Jensen, T. (2020). A systematic review of algorithm aversion in augmented decision making. *Journal of Behavioral Decision Making*, 33(2), 220–239. https://doi.org/10.1002/bdm.2155

Calvino, F., & Virgillito, M. (2018). The innovation-employment nexus: A critical survey of theory and empirics. *Journal of Economic Surveys*, 32(1), 83–117. https://doi.org/10.1111/joes.12190

Carlile, P. (2004). Transferring, translating, and transforming: An integrative framework for managing knowledge across boundaries. *Organization Science*, 15(5), 555–568. https://doi.org/10.1287/orsc.1040.0094

Cecez-Kecmanovic, D., Galliers, R., Henfridsson, O., Newell, S., & Vidgen, R. (2014). The sociomateriality of information systems: Current status, future directions. *MIS Quarterly*, 38(3), 809–830. https://doi.org/10.25300/MISQ/2014/38:3.3

Clark, A., & Chalmers, D. (1998). The extended mind. *Analysis*, 58(1), 7–19. https://doi.org/10.1093/analys/58.1.7

Daily, M., Oulasvirta, A., & Rekimoto, J. (2017). Technology for human augmentation. *Computer*, 50(2), 12–15. https://doi.org/10.1109/MC.2017.39

Davenport, T., & Kirby, J. (2015). Beyond automation. *Harvard Business Review*, June 2015, 58–65. https://hbr.org/2015/06/beyond-automation

Davenport, T., & Kirby, J. (2016). *Only humans need apply: Winners and losers in the age of smart machines*. Harper Business.

De Preester, H. (2011). Technology and the body: The (im)possibilities of re-embodiment. *Foundations of Science*, 16, 119–137. https://doi.org/10.1007/s10699-010-9188-5
Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. (2019). Hybrid intelligence. *Business Information Systems Engineering*, 61(5), 637–643. https://doi.org/10.1007/s12599-019-00595-2
Dwivedi, Y., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P., Janssen, M., Jones, P., Kar, A., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. (2019). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 1–47. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
Engelbart, D. (1962). *Augmenting human intellect: A conceptual framework* (Summary Report AFOSR-3223). Stanford Research Institute. https://www.dougengelbart.org/content/view/138/
Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization*, 28(1), 62–70. https://doi.org/10.1016/j.infoandorg.2018.02.005
Faraj, S., & Pachidi, S. (2021). Beyond uberization: The co-constitution of technology and organizing. *Organization Theory*, 2(1), 1–14. https://doi.org/10.1177/2631787721995205
Farrow, E. (2017). To augment human capacity—Artificial intelligence evolution through causal layered analysis. *Futures*, 108, 61–71. https://doi.org/10.1016/j.futures.2019.02.022
Fitzgerald, M., Boddy, A., & Baum, S. (2020). *2020 survey of artificial general intelligence projects for ethics, risk, and policy* (Technical Report 20-1). Global Catastrophic Risk Institute. https://gcrinstitute.org/papers/055_agi-2020.pdf
Frey, C., & Osborne, M. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019
Gal, U., Jensen, T., & Stein, M-K. (2020). Breaking the vicious cycle of algorithmic management: A virtue ethics approach to people analytics. *Information and Organization*, 30(2), 1–15. https://doi.org/10.1016/j.infoandorg.2020.100301
Gerber, A., Derckx, P., Döppner, D., & Schoder, D. (2020). Conceptualization of the human-machine symbiosis - A literature review. *Proceedings of the 53rd Hawaii International Conference on System Sciences*, 289–298. https://doi.org/10.24251/HICSS.2020.036
Goldin, C., & Katz, L. (1998). The origins of technology-skill complementarity. *Quarterly Journal of Economics*, 113(3), 693–732. https://doi.org/10.1162/003355398555720
Grace, K., Salvatier, J., Dafoe, A., Zhang, B., & Evans, O. (2018). Viewpoint: When will AI exceed human performance? Evidence from AI experts. *Journal of Artificial Intelligence Research*, 62, 729–754. https://doi.org/10.1613/jair.1.11222
Grigsby, S. (2018). Artificial intelligence for advanced human-machine symbiosis. In D. Schmorrow, & C. Fidopiastis (Eds.), *Augmented cognition: Intelligent technologies* (p. 255–266), Springer.
Grønsund, T., & Aanestad, M. (2020). Augmenting the algorithm: Emerging human-in-the-loop work configurations. *Journal of Strategic Information Systems*, 29(2), 1–16. https://doi.org/10.1016/j.jsis.2020.101614
Hassani, H., Silva, E., Unger, S., TajMazinani, M., & MacFeely, S. (2020). Artificial intelligence (AI) or intelligence augmentation (IA): What is the future? *AI*, 1(2), 143–155. https://doi.org/10.3390/ai1020008
Hernández-Orallo, J., & Vold, K. (2019). AI extenders: The ethical and societal implications of humans cognitively extended by AI. *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society (AIES'19)*, 507–513. https://doi.org/10.1145/3306618.3314238
Holzinger, A. (2016). Interactive machine learning for health informatics: when do we need the human-in-the-loop? *Brain Informatics*, 3, 119–131. https://doi.org/10.1007/s40708-016-0042-6
Huysman, M. (2020). Information systems research on artificial intelligence and work: A commentary on "Robo-Apocalypse cancelled? Reframing the automation and future of work debate". *Journal of Information Technology*, 35(4), 307–309. https://doi.org/10.1177/0268396220926511
Ihde, D. (1979). Technics and Praxis. *Studies in Soviet Thought*, 23(4), 337–339.
Järvelin, K., & Repo, A. (1982). Knowledge work augmentation and human information seeking. *Journal of Information Science*, 5(2-3), 79–86. https://doi.org/10.1177/016555158200500204
Kellogg, K., Valentine, M., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, 14(1), 366–410. https://doi.org/10.5465/annals.2018.0174

Keynes, J. (1930). Economic possibilities for our grandchildren. In J. Keynes (Ed.), *Essays in Persuasion* (pp. 358–373), W.W. Norton.
Kim, B., Koopmanschap, I., Mehrizi, M., Huysman, M., & Ranschaert, E. (2021). How does the radiology community discuss the benefits and limitations of artificial intelligence for their work? A systematic discourse analysis. *European Journal of Radiology*, 136, 1–6. https://doi.org/10.1016/j.ejrad.2021.109566
Kiran, A. (2015). Four dimensions of technological mediation. In R. Rosenberger, & P. Verbeek, (Eds.), *Postphenomenological investigations: Essays on human–technology relations* (pp. 123–140). Lexington Books.
Korinek, A., & Stiglitz, J. (2021). *Steering technological progress*. RCEA. http://rcea.org/wp-content/uploads/2021/04/Future-of-growth/Korinek.pdf
Kusters, R., Misevic, D., Berry, H., Cully, A., Le Cunff, Y., Dandoy, L., Díaz-Rodríguez, N., Ficher, M., Grizou, J., Othmani, A., Palpanas, T., Komorowski, M., Loiseau, P., Moulin Frier, C., Nanini, S., Quercia, D., Sebag, M., Soulié Fogelman, F., Taleb, S., ... Wehbi, F. (2020). Interdisciplinary research in artificial intelligence: Challenges and opportunities. *Frontiers in Big Data*, 3, 1–7. https://doi.org/10.3389/fdata.2020.577974
Lebovitz, S., Lifshitz-Assaf, H., & Levina, N. (2022). To engage or not to engage with AI for critical judgments: How professionals deal with opacity when using AI for medical diagnosis. *Organization Science*, 33(1), 126–148. https://doi.org/10.1287/orsc.2021.1549
Licklider, J. (1960). Man-computer symbiosis. *IRE Transactions on Human Factors in Electronics*, 1(1), 4–11. https://doi.org/10.1109/THFE2.1960.4503259
Luong, A., Kumar, N., & Lang, K. (2019). Man-machine collaboration in organizational decision-making: An experimental study using loan application evaluations. *Proceedings of the 2019 Pre-ICIS SIGDSA Symposium*, 1–4. https://aisel.aisnet.org/sigdsa2019/
Lyytinen, K., & Grover, V. (2017). Management misinformation systems: A time to revisit? *Journal of the Association for Information Systems*, 18(3), 206–230. https://doi.org/10.17705/1jais.00453
Merleau-Ponty, M. (1945). *Phénoménologie de la perception*. Gallimard.
Murray, A., Rhymer, J., & Sirmon, D. (2020). Humans and technology: Forms of conjoined agency in organizations. *Academy of Management Review*, 46(3), 552–571. https://doi.org/10.5465/amr.2019.0186
Orlikowski, W., & Scott, S. (2008). Sociomateriality: Challenging the separation of technology, work, and organization. *Academy of Management Annals*, 2(1), 433–474. https://doi.org/10.1080/19416520802211644
Østerlund, C., Crowston, K., & Jackson, C. (2020). Building an apparatus: Refractive, reflective and diffractive readings of trace data. *Journal of the Association for Information Systems*, 21(1). https://doi.org/10.17705/1jais.00590
Plastino, E., & Purdy, M. (2018). Game changing value from artificial intelligence: Eight strategies. *Strategy & Leadership*, 46(1), 16–22. https://doi.org/10.1108/SL-11-2017-0106
Rai, A., Constantinides, P., & Sarker, S. (2019). Next generation digital platforms: Toward human-AI hybrids. *MIS Quarterly*, 43(1), iii–ix.
Raisamo, R., Rakkolainen, I., Majaranta, P., Salminen, K., Rantala, J., & Farooq, A. (2019). Human augmentation: Past, present and future. *International Journal of Human-Computer Studies*, 131, 131–143. https://doi.org/10.1016/j.ijhcs.2019.05.008
Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review*, 46(1), 192–210. https://doi.org/10.5465/amr.2018.0072
Raj, M., & Seamans, R. (2019). Primer on artificial intelligence and robotics. *Journal of Organization Design*, 8(11), 1–14. https://doi.org/10.1186/s41469-019-0050-0
Rouse, W., & Spohrer, J. (2018). Automating versus augmenting intelligence. *Journal of Enterprise Transformation*, 8(1-2), 1–21. https://doi.org/10.1080/19488289.2018.1424059
Russell, S., & Norvig, P. (2016). *Artificial intelligence: A modern approach* (3rd ed.). Prentice Hall Press.
Ryder, A. (2017, June 19). Augmentation versus automation: AI's utility in the workplace. *MIT Sloan Management Review*. https://sloanreview-mit-edu.vu-nl.idm.oclc.org/article/augmentation-versus-automation-ais-utility-in-the-workplace/
Sampson, S. (2020). A strategic framework for task automation in professional services. *Journal of Service Research*, 24(1), 122–140. https://doi.org/10.1177/1094670520940407

Sergeeva, A., Faraj, S., & Huysman, M. (2020). Losing touch: An embodiment perspective on coordination in robotic surgery. *Organization Science*, 31(5), 1248–1271. https://doi.org/10.1080/19488289.2018.1424059

Simon, H. (1965). *The shape of automation for men and management*. Harper & Row.

Skagestad, P. (1993). Thinking with machines: Intelligence augmentation, evolutionary epistemology, and semiotic. *Journal of Social and Evolutionary Systems*, 16(2), 157–180.

Skinner, A., Russo, C., Baraniecki, L., & Maloof, M. (2014). Ubiquitous augmented cognition. *8th International Conference on Foundations of Augmented Cognition. Advancing Human Performance and Decision-Making through Adaptive Systems,* 8534, 67–77. https://doi.org/10.1007/978-3-319-07527-3_7

Teodorescu, M., Morse, L., Awwad, Y., & Kane, G. (2021). Failures of fairness in automation require a deeper understanding of human-ML augmentation. *MIS Quarterly*, 45(3), 1483–1500. https://doi.org/10.25300/MISQ/2021/16535

Tschang, F., & Almirall, E. (2021). Artificial intelligence as augmenting automation: Implications for employment. *Academy of Management Perspectives*, 35(4), 642–659. https://doi.org/10.5465/amp.2019.0062

Van den Broek, E., Sergeeva, A., & Huysman, M. (2021). When the machine meets the expert: An ethnography of developing AI for hiring. *MIS Quarterly*, 45(3), 1557–1580. https://doi.org/10.25300/MISQ/2021/16559

Von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries*, 4(4), 404–409. https://doi.org/10.5465/amd.2018.0084

Waardenburg, L. (2021). *Behind the scenes of artificial intelligence: Studying how organizations cope with machine learning in practice*. Haveka.

Waardenburg, L., Huysman, M., & Agterberg, M. (2021). *Managing AI wisely: From development to organizational change in practice*. Edward Elgar Publishing.

Waardenburg, L., Huysman, M., & Sergeeva, A. (2022). In the land of the blind, the one-eyed man is king: Knowledge brokerage in the age of learning algorithms. *Organization Science*, 33(1), 59–82. https://doi.org/10.1287/orsc.2021.1544

Wilson, H., & Bataller, C. (2015, May 27). How people will use AI to do their jobs better. *Harvard Business Review*. https://hbr.org/2015/05/how-people-will-use-ai-to-do-their-jobs-better

Wilson, H., & Daugherty, P. (2018). Collaborative intelligence: Humans and AI are joining forces. *Harvard Business Review*, July-August 2018, 114–123. https://hbr.org/2018/07/collaborative-intelligence-humans-and-ai-are-joining-forces

Xia, C., & Maes, P. (2013). The design of artifacts for augmenting intellect. *Proceedings of the 4th Augmented Human International Conference*, 154–161. https://doi.org/10.1145/2459236.2459263