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Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making

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Abstract Artificial intelligence (AI) has penetrated many organizational processes, resulting in a growing fear that smart machines will soon replace many humans in decision making. To provide a more proactive and pragmatic perspective, this article highlights the complementarity of humans and AI and examines how each can bring their own strength in organizational decision-making processes typically characterized by uncertainty, complexity, and equivocality. With a greater computational information processing capacity and an analytical approach, AI can extend humans' cognition when addressing complexity, whereas humans can still offer a more holistic, intuitive approach in dealing with uncertainty and equivocality in organizational decision making. This premise mirrors the idea of intelligence augmentation, which states that AI systems should be designed with the intention of augmenting, not replacing, human contributions.

1. The buzz around artificial intelligence

Artificial Intelligence's (AI's) visibility and rapid momentum in recent years is best reflected in IBM's Watson's[1] defeat of *Jeopardy's* top human contenders and Google DeepMind's AlphaGo,[2] which trounced one of the world's best at the board game Go. There are many variations of AI but the concept can be defined broadly as intelligent systems with the ability to think and learn (Russell, Norvig, & Intelligence, 1995). AI embodies a heterogeneous set of tools, techniques,

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[1] https://www.ibm.com/watson
[2] https://deepmind.com/research/alphago

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and algorithms. Various applications and techniques fall under the broad umbrella of AI, ranging from neural networks to speech/pattern recognition to genetic algorithms to deep learning. Examples of common elements that extend AI cognitive utilities and can augment human work include natural language processing (the process through which machines can understand and analyze language as used by humans), machine learning (algorithms that enable systems to learn), and machine vision (algorithmic inspection and analysis of images).

Natural language processing affords IBM's Watson the ability to understand nuanced human-composed sentences and assign multiple meanings to terms and concepts. Machine learning capabilities empower Watson to learn from experience and interaction with data, and to develop intelligent solutions based on past experiences. Through machine learning techniques and access to medical research articles, electronic medical records, and even doctors' notes at Memorial Sloan Kettering, Watson has learned to discern cancer patterns. The AI has made headway in offering promising courses of treatment. AI-powered machine vision, finally, has enabled Watson to rapidly process myriads of MRI images of the brain and to mark very small hemorrhages in the image for doctors (Captain, 2017).

Emerging AI systems like Watson possess an exceptional ability to learn and improve themselves, accelerating their use for some knowledge-based tasks that not long ago were seen as the exclusive domain of humans. These tasks were once performed by white-collar workers and were viewed as immune to automation (Wladawsky-Berger, 2017). The intelligence of AI technologies is expanding rapidly, and they are acting as semiautonomous decision makers in complex, increasingly diverse contexts (Davenport & Kirby, 2016). Postindustrial economies are now entering a second machine age thanks to advanced smart technologies that are on course to displace human workers across multiple fields (Brynjolfsson & McAfee, 2014).

As AI applications continue to proliferate, organizations are faced with vexing questions about AI's influence on work. It is argued that "for any given skill one can think of, some computer scientist may already be trying to develop an algorithm to do it" (MacCrory, Westerman, Alhammadi, & Brynjolfsson, 2014, p. 14). People like Elon Musk stress the magnitude of disruption caused by AI and suggest AI will take over most human jobs (Leetaru, 2016). Along these lines, AI and other smart technologies are often discussed as being at the epicenter of an unprecedented wave of automation. They are seen as drivers for the transformation of decision making as a cognitive and information-centric process (Kelly, 2012; MacCrory et al., 2014). Executives from America's largest corporations ranked AI and machine learning as the most disruptive forces in the business landscape of the near future (New Vantage Partners, 2017), and a recent survey by Accenture (2017) revealed that 85% of surveyed executives have plans to invest extensively in AI-related technologies over the next 3 years.

1.1. How we talk about AI

It is important to place the fascination with AI capabilities, along with its inertial proclivity toward automation and displacement of humans, in a historical context. In 1930, the prominent 20th century economist John Maynard Keynes described "technological unemployment" as a "new disease" (Wladawsky-Berger, 2017). Later, Zuboff (1988) engaged with the work implications of information technologies. She presented information technologies as smart technologies and distinguished them from mechanization and automation. She described information technologies as the activation of a process through which activities, objects, and events are translated into information (Zuboff, 1988). Even though information technologies have promising affordances, such as providing a deeper level of transparency and creating a more rewarding workplace, Zuboff shared similar disadvantages when these technologies were used exclusively as a means of automation and control. For that reason, automation has been an object of popular discussion for decades among both academics and business practitioners.

Whereas the recent hyperbole surrounding AI and other cognitive technologies has led many to believe that machines will soon outthink humans and replace them in the workplace, others see the concern around AI as another overhyped proposition (Guszcza, Lewis, & Evans-Greenwood, 2017). In fact, such inflated arguments are not entirely new, and call to mind early predications made in the wake of the first AI research and breakthroughs regarding the use of AI in future work. Celebrated cognitive scientist Herbert Simon (1965) predicted that smart machines would be capable of achieving any work that a human can do by 1985. Marvin Minsky, founder of MIT's AI Lab, made an even more audacious projection in 1970 about the future of AI (King & Grudin, 2016, p. 83):

> In from 3 to 8 years we will have a machine with the general intelligence of an average human being . . . able to read Shakespeare, grease a car, play office politics, tell a joke,

> and have a fight. At that point, the machine will begin to educate itself with fantastic speed. In a few months, it will be at genius level and a few months after that its powers will be incalculable.

What is lacking in this old discourse, as well as with the recent attention paid to AI, is a discussion of how the unique strengths of humans and AI can act synergistically. This article builds upon pronouncements from some AI pioneers that "computers plus humans do better than either one alone" (Campbell, 2016), and explores the complementarity of humans and AI in the context of organizational decision making.

Chess provides an example. Even chess masters' abilities to predict and process contingencies in the game is largely limited by their cognitive capacities; they are believed to only consider 100 contingencies (almost 10% of the possibilities of a move and response; Simon, 1982). AI has long surpassed this constrained cognitive capacity, beginning with IBM Deep Blue's 1997 defeat of Gary Kasparov, a chess grandmaster at the time. This marked the beginning of a new era, and many predicted the end of the game of chess. However, when Kasparov developed his own vision of a new chess league (similar to the idea of freestyle martial arts), the best chess player was neither AI nor human. They were what he called centaurs, essentially partnerships between humans and AI. The example of chess proposes a vision for the complementary roles of humans and AI; they offer different yet complementary capabilities needed for effective decision making.

The synergic partnership between AI and humans is not unique to the game of chess; it can be observed elsewhere (Brynjolfsson & McAfee, 2012). Another example comes from a recent study of cancer detection in the images of lymph node cells (Wang, Khosla, Gargeya, Irshad, & Beck, 2016). An AI-exclusive approach had a 7.5% error rate and pathologists had a 3.5% error rate; however, an approach combining inputs from both AI and pathologists resulted in an error rate of 0.5% (85% reduction in error). These examples bring us back to the vision of human-machine symbiosis articulated by J. C. R. Licklider, a relationship through which the strengths of one compensate for the limitations of the other.

1.2. Who, or what, makes a better decision maker?

With the resurgence of AI, a new human-machine symbiosis is on the horizon and a question remains: How can humans and new artificial intelligences be complementary in organizational decision making? To address this basic question, I draw upon the distinction between analytical and intuitive decision making, and the three challenges that plague decision making in organizations: uncertainty, complexity, and equivocality (Choo, 1991; Simon, 1982).

Organizational scholars have distinguished between analytical and intuitive practices used in processing information and arriving at a decision by studying the daily practices of managers and other organizational members (Dane, Rockmann, & Pratt, 2012). By employing an analytical approach, individuals can engage in methodical, laborious information gathering and analysis, and develop alternative solutions in an attentive fashion. An analytical approach often involves analyzing knowledge through conscious reasoning and logical deliberation. The problem-solving ability of AI is more useful for supporting analytical rather than intuitive decision making. As noted, AI encompasses a broad range of applications and algorithms. For the purposes of this article, I focus on analytical AI applications and techniques that imitate and extend the way humans reason and the way they use reasoning to draw conclusions from masses of information. For example, AI tools such as expert systems and predictive analytics provide affordances for well-deliberated calculations that integrate otherwise unmanageable amounts of data; these tools produce analyses and help evaluate alternative decision options.

However, much of cognition and human decision making is not a direct result of deliberate information gathering and processing, but instead arises from the subconscious in the realm of intuition (Dane et al., 2012). Intuition, in a decision-making context, is defined as a capacity for generating direct knowledge or understanding and arriving at a decision without relying on rational thought or logical inference (Sadler-Smith & Shefy, 2004). Superior intuition can be understood as a gut feeling or business instinct about the outcome of an investment or a new product. Intuitive decision making includes imagination, sensitivity, rumination, creativity, and what psychologists such as Carl Jung considered *intuitive intelligence*: the human capacity to analyze alternatives with a deeper perception, transcending ordinary-level functioning based on simple rational thinking (Bishop, 2000). Through an intuitive approach, the individual draws upon past embodied practices, experiences, and judgments to react or decide without conscious attention. Whereas analytical approaches to decision making rely on depth of information, intuitive approaches focus on breadth by engaging a problem with a holistic and abstract view. These two styles are not mutually exclusive and are employed as parallel systems of decision making to more effectively address various contingencies.

While AI systems support an analytical decision-making approach, they are less capable of understanding common-sense situations (Guszcza et al., 2017) and compared to humans they are less viable in uncertain or unpredictable environments—particularly outside of a predefined domain of knowledge (Brynjolfsson & McAfee, 2012). Bernie Meyerson, IBM's chief innovation officer, said (Captain, 2017): "Humans bring common sense to the work; by its definition, common sense is not a fact-based undertaking. It is a judgment call." Humans tend to perform better in the face of decisions that require an intuitive approach. In the following sections, I present AI, embodying an analytical approach, as more effective in overcoming complexity in decision making than humans. Though AI does have superior qualities, humans retain the comparative advantage when addressing uncertainty and equivocality in decision making as they can leverage their superior intuition, imagination, and creativity.

2. The uncertainty of decision making

Uncertainty is characterized as a lack of information about all alternatives or their consequences, which makes interpreting a situation and making a decision more difficult (Choo, 1991). Uncertainty can stem from a lack of information about both internal and external organizational environments (e.g., shortage of human resources, emergence of disruptive technologies, new markets and competitors, new government policies). AI and other intelligent technologies can assist human decision makers with predictive analytics: (1) they can generate fresh ideas through probability and data-driven statistical inference approaches and (2) identify relationships among many factors, which enables human decision makers to more effectively collect and act upon new sets of information. One of the primary functions of predictive analytics is generating new information and predictions about customers, assets, and operations.

Consulting firms such as Deloitte and McKinsey have already developed intelligent tools that offer monitoring and sensing of an organization's external environment, enabling semiautomated strategy articulation. AI systems can help managers detect anomalies by providing real-time insight about early warning signs of bigger issues that allows for the possibility of timely corrective actions. An example of this is Moore's (2016) suggestion that the detailed maintenance log of a fleet of aging F-16 fighters be analyzed by AI algorithms to identify patterns of failures that may currently affect only a handful of aircrafts, but have the potential to turn into more prevalent problems in the future.

2.1. Intuitive decision making: The human advantage

When the ambiguity is overwhelming—as is the case in much organizational decision making—or when organizations are faced with situations for which there is no precedent, an intuitive style of decision making may prove more helpful. This characterizes many organizational decisions, wherein "the ratio of examples of past similar decisions to stuff that might be important for those decisions is often abysmally low" (Ransbotham, 2016). Problems ranging from global crises to technical glitches can disrupt decisions and strategies made through the most information-centric, rational processes. Cognitive technologies can analyze probability-based decision contexts, but are ill equipped to tackle novel problems and situations (Guszcza et al., 2017). Unlike board games, in which the probability of the next action can be calculated, real-world decision making is messy and reliance on probabilistic, analytical thinking tends to be insufficient (Campbell, 2016). In this context, human decision makers often build on an intuitive approach, leveraging insight and qualitative assessment that is rooted in years of tacit experience and personal judgement. It is very difficult to articulate the reasons behind these decisions beyond that they just feel right (Sadler-Smith & Shefy, 2004).

Humans continue to excel in making decisions regarding real-world problems riddled with uncertainty. When it comes to deciding on new products, Apple rarely considers studies, surveys, or extensive research. It is unusual for a major decision to take several months; instead, Steve Jobs became known for making quick but intuitive decisions. In the case of the first iMacs, Steve Jobs immediately decided that Apple should release the new computers in a rainbow of candy colors. Jony Ive, Apple's chief design officer, noted: "In most places that decision would have taken months. Steve did it in a half hour" (Isaacson, 2011, p. 356). This indicates that the ingenuity and creativity of Jobs' decisions did not necessarily lie in processing informational inputs and understanding the probability of success, but in coming up with solutions that looked holistically sensible based on his gut feeling. In doing so, Jobs shaped both the consumer technology market and customers' tastes. His decisions were not always a success (e.g., choosing the wrong market for NeXT computers and launching failing products such as Macintosh TV); however, a strong intuition is driven in part by tacit learning from previous mistakes and experimentations.

Beyond Apple, prioritizing intuition over analytical data is pervasive among senior decision makers. Ralph Larsen, then-CEO of Johnson & Johnson, described his approach as follows (Hayashi, 2001):

> Very often, people will do a brilliant job up through the middle management levels, where it's very heavily quantitative in terms of the decision making. But then they reach senior management, where the problems get more complex and ambiguous, and we discover that their judgment or intuition is not what it should be. And when that happens, it's a problem; it's a big problem.

Abstract thinking and an intuitive approach can handle unconventional and creative decision-making situations (Gardner & Martinko, 1996). This inherent, inexplicable perception that comes from within is almost impossible to simulate with AI (Parikh, Lank, & Neubauer, 1994). Machines are mostly incapable of capturing the inner logic and subconscious patterns of human intuition. Therefore, AI is less likely to mimic human problem solving in these areas. Humans tend to keep their comparative advantage in situations that require holistic and visionary thinking. This may be found in more senior levels of organizations, since strategic planning activities may involve higher levels of ambiguity and uncertainty (Sadler-Smith & Shefy, 2004).

3. Addressing complexities in decision making: The AI advantage

Complex situations are characterized by an abundance of elements or variables. They demand the processing of masses of information at a speed beyond the cognitive capabilities of even the smartest human decision makers. In recent years, AI with superior quantitative, computational, and analytical capabilities has surpassed humans in complex tasks. Coupled with big data, algorithmic decision making has opened up new opportunities for dealing with complexity and presents more effective ways of equipping human decision makers with comprehensive data analytics. AI has the advantage of brute force, making it a rigorous tool for retrieving and analyzing huge amounts of data, ameliorating the complexity of a problem domain. For example, AI can help reduce the complexity of a problem by identifying causal relationships and asserting the appropriate cause of action among many possibilities through causal loops (if this, then act so; Marwala, 2015).

AI has the potential for a myriad of contributions, including assessing a person's credit risk by examining his/her friend list on Facebook, pricing ads in digital marketing, and underwriting mortgages in the U.S. real estate industry. In recent years, the advent of deep learning has taken this to a completely new level by enabling the machine to learn from raw data itself and expand by integrating larger data sets. In these complex situations, there may be too much data for humans to master; machines consistently deliver higher decision quality.

3.1. An opportunity for partnership

One way to materialize the synergistic relationship between AI and humans is to combine the speed of AI in collecting and analyzing information with humans' superior intuitive judgement and insight. There are several examples of this relationship. Correlation Ventures, a venture capital firm that finances startups, assesses investment opportunities in 2 weeks by utilizing the predictive power of AI analytics that seamlessly process large amounts of data, combined with a more holistic review of the results by human experts. Bots now detect inappropriate or controversial web or social media content by combing through and processing terabytes of user-generated data, but the final decision to remove social media posts or videos often rests with the on-demand workers "behind the AI curtain" who use superior human judgement (Gray & Suri, 2017). Reid Hoffman, executive chairman of LinkedIn, said AI systems enable humans to make better decisions because AI "can sift through vast amounts of data to highlight the most interesting things, at which point managers can drill down, using human intelligence, to reach conclusions and take actions" (Hoffman, 2016).

4. Overcoming equivocality in decision making

Equivocality refers to the presence of several simultaneous but divergent interpretations of a decision domain (Weick & Roberts, 1993). Equivocality often occurs due to the conflicting interests of stakeholders, customers, and policy makers. This transforms decision making from an impartial, objective process (as assumed in an analytical, rational approach) into an inherently subjective and political process that attempts to fulfill the conflicting needs and objectives of multiple parties. Even the most analytically calculated rational decision can be stymied in practice by parties whose power and interests are affected by the intended and unintended consequences of a decision.

AI can furnish some utilities that enable decision makers to overcome equivocal situations and address relevant conflicting needs. For example, AI systems that conduct sentiment analyses of both internal and external channels (e.g., social media) tend to provide a more precise reflection of possible reactions to organizational decisions. Nevertheless, handling equivocality is predominantly the responsibility of human actors. They will likely retain their superior capabilities in deciphering the political landscape both inside and outside the organization, and in building the required invisible foundation for successfully making, negotiating, and implementing decisions (e.g., building coalitions, alliances). Even if machines can determine the optimal decision, they are less likely to be able to sell it to a diverse set of stakeholders. Recall my earlier example of chess. Murray Campbell (2016), a key member of the IBM Deep Blue project, asserted:

> Chess computers make moves that sometimes make no sense to their human opponents. They [still] don't have any sense of aesthetics . . . They play what they think is the objectively best move in any position, even if it looks absurd, and they can play any move no matter how ugly it is.

The objective, impersonal approach of the machine can be at odds with the subjective, emotionally charged, and contextually sensitive nature of many intuitive decisions made in organizations. Both formal and informal leaders are consequential in rallying people toward a decision by rendering it compatible with varying priorities.

A key capacity of organizational leaders is the ability to develop viable visions and objectives, and then to convince others (both their employees and external stakeholders) of the indispensability of their decisions. This requires emotional and social intelligence, which in turn serves as a foundation for putting interpersonal skills into practice. In addition, informal leaders (not necessarily managers with formal power) play a key role in dealing with the equivocality of decision making. Organization scientists have long regarded informal leaders as well positioned to align people's interests, iron out possible conflicts, and build consensus by the virtue of their social ties, skills, and their delicate understanding of the social fabrics of their organizations (Cross, Borgatti, & Parker, 2002). The responsibility of dissecting the labyrinth of complex social systems tends to lie outside the capacity of AI. Parry, Cohen, and Bhattacharya (2016, p. 583) doubt that organizational members "will 'follow' the AI system in the same manner that they could be expected to follow the compelling story of a capable human leader." Hence, humans continue to enjoy a comparative advantage in understanding the convoluted social and political dynamics underlying equivocal decision-making situations, and to outperform machines in such social mechanisms as persuasion and negotiation.

4.1. A balanced approach

It is important to note that the decision-making process often involves all three characteristics discussed—uncertainty, complexity, and equivocality (Koufteros, Vonderembse, & Jayaram, 2005)—and these characteristics should not be understood as mutually exclusive. Most organizational decision making is best handled by using a blend of both analytical and intuitive approaches (Hung, 2003). Martin (2009, p. 6) put this succinctly: "Aspects of both analytical and intuitive thinking are necessary but not sufficient for optimal business performance. The most successful businesses in the years to come will balance analytical mastery and intuitive originality." One manager, cited by Burke and Miller (1999, p. 93), provided an explanation as to why reliance on either analysis or intuition alone is insufficient, particularly when it comes to convincing others in collaborative decision making:

> Every decision is a combination of deduction and intuition. I believe that intuition isn't particularly useful all by itself. I suppose you could run into managers who believe intuition means pulling an answer out of the air . . . I don't think intuition can operate unless there is data available to you that you can process and combine with past experience [as the driver of intuition] and also with data-driven analysis.

The most complex decisions may still encapsulate an element of uncertainty, thus rendering human input indispensable. For example, with their intuitive approaches humans can ascertain what variables or future events (out of endless factors) may more strongly influence outcomes. This helps to identify what factors must be foregrounded in data collection and analysis, which will be the primary undertaking of smart technologies. Moreover, analysis in many cases may result in multiple alternate routes with almost equal factual supports; humans can help in choosing the one that appears to be more intuitively sensible. Consequently, the partnership between human decision makers and AI and can play out in two ways:

1. Humans and AI technologies can collaborate to deal with different aspects of decision making. AI is likely to be well positioned to tackle complexity issues (using analytical approaches).

Humans can focus more on uncertainty and equivocality, using more creative and intuitive approaches.

2. Even the most complex decisions—of which AI has a comparative edge—are likely to require elements of uncertainty and equivocality, which compels human involvement. Therefore, humans and AI will play a combined role in almost all complex decision making (see Figure 1).

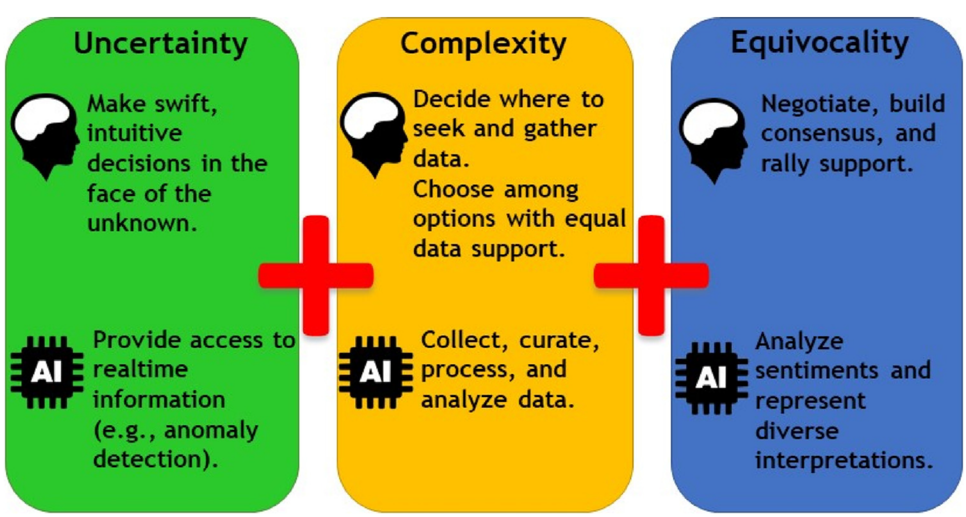
5. Implications for managers and organizations

In AI-enabled business investments, the way many managers justify return on investment (ROI) in cognitive technologies centers on significant and immediate headcount reduction (Davenport & Faccioli, 2017). My premise in this article is that most benefits of AI are likely to materialize only in long-term partnership with unique human capabilities. As such, appraising the business value of AI adoption takes patience and a long-term perspective rather than relying on short-term ROI consideration for assessing immediate financial impacts. Viewing and approaching AI as a panacea is shortsighted. Decades of research outlines the ways in which organizations are complicated sociotechnical systems and technological breakthroughs prevail only if they are judiciously integrated into the social fabrics of an organization (Sawyer & Jarrahi, 2014). AI is no exception.

Studies of previous technology-centered initiatives (i.e., business process reengineering) suggest that short-term financial gains from replacing humans can be ephemeral and thwarted by more profound and less visible effects such as a demoralized workforce (Mumford, 1994). The vision of human-AI symbiosis set forth in this article calls for proactively identifying areas in which AI can augment rather than simply replace humans in decision making or manage them algorithmically. Procter & Gamble and American Express provide useful examples. Both firms have engaged with AI for years now, but their overall strategies have not been to just automate processes or eliminate human jobs. Instead, they view and employ AI as a tool from which employees can draw to do their work (Davenport & Bean, 2017). This is in contrast to a prevalent modern-day Taylorism embodied in many forms of algorithmic management, which intentionally or unintentionally aspires to deskill workers, treating them as "programmable cogs in machines," or removing them altogether from organizational processes for the sake of efficiency (Frischmann & Selinger, 2017).

Human-AI symbiosis means interactions between humans and AI can make both parties smarter over time. Most AI algorithms can learn and accelerate their utility with more exposure to data and interaction with human partners. Likewise, human decision makers are also likely to develop, over time, a more nuanced understanding of cognitive machines—how they operate and how they can contribute to decision making. Cognitive technologies can also provide support for humans to develop greater analytical skills. For example, a recent experiment at Yale University involving an online game suggested that smart bots helped teams of human players boost their performance (Shirado & Christakis, 2017). The technology aided performance by shortening the median time for human teams to solve problems by 55.6%.

Figure 1. Complementarity of humans and AI in decision-making situations, typically characterized by uncertainty, complexity, and equivocality



As AI evolves and improves over time, managers and employees have to adapt and readapt. To keep a balanced human-AI symbiosis, human decision makers must continuously update their AI literacy (e.g., how to invoke and put into practice the most recent AI developments) as well as their own comparative edge in this partnership (e.g., intuition, holistic vision, and emotional intelligence). Even though intuitive capabilities are the primary advantage of humans in decision making, they still need to nurture analytical skills. In order to be AI literate, humans should develop an appreciation of how analytical decisions are made by cognitive technologies and work out how to integrate the analytical capabilities offered by these technologies into organizational processes. The focus on analytical skills in formal academic training (e.g., MBA curricula) as well as in on-the-job learning is not likely to go away. In fact, a key element that helps humans trust and interact more effectively with smart technologies is knowing how these technologies come up with analytical decisions or recommendations (Davenport & Kirby, 2016). Making this process transparent enhances human-AI interaction and provides opportunities for humans to foster analytical skills.

Finally, to embrace AI's promises, digital transformation strategies should reimagine work and decision making around distinctively human or artificial capabilities. More specifically, an effective AI strategy should (1) build from current strategic strengths and (2) identify ways AI and knowledge workers can complement one another. For example, General Electric (GE) has been going through a substantial digital transformation over the past years, morphing from an industrial product and service firm to a digital industrial one. In this context, GE has been able to use AI technologies to generate insights by making sense of the massive amounts of data produced or captured by an enormous quantity of industrial devices (as legacy systems). One of the clear outcomes is the optimization of decisions relative to operations and supply chains by more effectively understanding how the equipment is run (CIO Network, 2017). In addition, to establish a working human-AI symbiosis, GE encourages and capitalizes on dual experts or hybrid scientists who are initially hired as subject experts (e.g., physicists, aerospace engineers, business analysts), but are then trained in machine learning or other areas of AI (through GE's certification program for data analytics). These individuals are likely to develop the most workable solutions for integrating AI in their respective lines of service. GE's objective is not to replace these experts but to help them harness the power of AI.

6. Summary: Call for a new human-machine collaboration

The rise of AI calls for a new human-machine symbiosis, which presents a shifting division of work between machines and humans. Pervasive visions of partnerships between humans and machines suggest that machines should take care of mundane tasks, allowing humans to focus on more creative work. Given the substantial improvement in AI capabilities in recent years, this article goes beyond this simple vision and advances the notion of human-machine collaboration by focusing on the comparative advantages held by humans and machines in relation to the three characteristics that affect almost all organizational decision making. Although AI capabilities help humans overcome complexity through a superior analytical approach, the role of human decision makers and their intuition in dealing with the uncertainty and equivocality of decision making remains unquestionable. Machines depend upon humans when subconscious decision heuristics are necessary to evaluate and facilitate the outcomes of decisions.

AI solutions have already overtaken humans in accomplishing some quantitative targets with computable criteria (Parry et al., 2016), thus alleviating the complexity of decision making. Humans will likely outperform AI in evaluating subjective, qualitative matters (e.g., norms, intangible political interests, and other complicated social, contextual factors). Past experience, insight, and holistic vision are, and will remain, human capitals; these are internalized as subconscious, automatic, and intuitive thinking processes that still offer humans unique positions in handling ambiguous and equivocal situations. Due to their intuitive capabilities, humans continue to perform better at big-picture thinking. Davenport (2016) attested that broader strategic questions require a holistic approach, which cannot be captured by data alone. Henry Mintzberg (1994, p. 108) presented strategic thinking as grounded in synthesis, creativity, and intuition; strategic thinking therefore primarily results in an "integrated perspective of [the organization]" rather than a "too-precisely articulated vision of direction." Cognitive technologies such as AI can certainly help, but strategic thinking in particular requires a level of sensemaking and understanding of the world beyond specific decision contexts of which only humans are capable. The likelihood is remote that AI will ever be able to learn, imitate, and replicate the personal experience, subconscious thought patterns, and personality traits of humans that drive superior intuitive decision making.

Such intuition, in most cases, is a nontransferable human attribute (Buchanan & O'Connell, 2006).

Upper management is not the only group that engages in intuitive decision making in organizations. Many knowledge workers, even at lower and nonmanagerial levels, constantly find themselves in novel situations (specifically characterized by uncertainty and equivocality), and therefore require visionary and intuitive thinking. Examples of these nonmanagerial roles include product designers (e.g., aiming for affective design), positions involving developing people (e.g., human resource experts specializing in training and organizational learning), market analysts, and other types of knowledge workers that may not necessarily take up an analytical, rational decision-making approach. In addition, organizational studies (e.g., Cross et al., 2002) make it clear that leaders may not be the same as formally assigned managers; in fact, lower level organizational members can occupy central positions in the informal network of organizational influence, and can play an irreplaceable role in rallying support to deal with the equivocality of decision making. As a result, decision making at lower levels is not necessarily tractable by AI capabilities.

This article contributes to an understanding of how AI can aid and augment, rather than replace, human decision making. As Kevin Kelly (2012) argued: "This is not a race against the machines . . . This is a race with the machines." In line with the vision of human-machine symbiosis, it is more meaningful to view AI as a tool for augmentation (extending human's capabilities) rather than automation (replacing them). This can serve as a more effective guide for the future rather than a preoccupation with superintelligent machines that can replicate every aspect of human intelligence and eventually replace them in the workplace. To achieve such strategic human-machine partnerships, human intervention is arguably inevitable (Davenport, 2016); therefore the possibility of having an exclusively AI-based organizational decision system is shortsighted.

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