Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision Making

Article *in* Business Horizons · July 2018

DOI: 10.1016/j.bushor.2018.03.007

Mohammad Hossein Jarrahi
University of North Carolina at Chapel Hill

Citation: Jarrahi, M.H. (2018) "Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision Making," *Business Horizons*. 61(4).

Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision Making

Mohammad Hossein Jarrahi

University of North Carolina, Chapel Hill
200 Manning Hall
Chapel Hill, NC 27599 USA
Phone: +1 (919) 962-8364
jarrahi@unc.edu

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': AI systems should be designed with the intention of augmenting, not replacing, human contributions.

Keywords: Artificial intelligence, decision making, human-machine symbiosis, human augmentation

Introduction

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

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

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).

Let's take the example of IBM's Watson. Natural language processing affords 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's 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 semi-autonomous decision makers in an increasing diversity of complex contexts (Davenport & Kirby, 2016). Brynjolfsson and McAfee (2014) suggest that postindustrial economies are now entering a "second machine age" thanks to advanced smart technologies that are on the course to displace human workers across multiple fields.

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 (Kalev, 2016). Along these lines, AI and other smart technologies are often discussed as being at the epicenter of an unprecedented wave of automation. Specifically 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 in the years to come (New Vantage Partners, 2017), and a recent survey by Accenture reveals that 85% of surveyed executives have plans to invest extensively in AI-related technologies over the next three years (Accenture, 2017).

However, it is important to place the fascination with AI capabilities, and its inertial proclivity towards automation and displacement of humans, in a historical context. The prominent 20th century economist, John Maynard Keynes, in his 1930 article, “Economic Possibilities for our Grandchildren,” described “technological unemployment” as a “new disease.” (Wladawsky-Berger, 2017). More recently, Shoshana Zuboff (1988) in her monumental book (“In the Age of the Smart Machine”) specifically engaged with the work implications of information technologies. She presented information technologies as “smart” technologies, and distinguished them from previous mechanization and automation technologies in that information technologies activate the “informating” process, through which activities, objects, and events are translated into information. Even though information technologies have promising affordances, such as providing a deeper level of transparency, and creating a more rewarding workplace, she shared similar disappointments 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 a wholesale fashion in the workplace, others see the concern around AI as another overhyped proposition (Sandy Pentland interviewed in 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. For example, 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: “In from three to eight 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.“ (King & Grudin, 2016). What is lacking in this old discourse, as well as the recently resurrected attention paid to AI, however, 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’ ability to predict and process contingencies in the game is largely bounded by their limited 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 bounded cognitive capacity, beginning with IBM Deep Blue’s 1997 defeat of Gary Kasparov, a grandmaster of 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 ‘free style’ 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, but complementary capabilities needed for effective decision-making.

The synergic partnership between AI and humans is not unique to the game of chess, and 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 percent error rate, and pathologists had a 3.5 percent error rate; however, an approach combining inputs from both AI and pathologists resulted in an error rate of 0.5 percent (85 percent 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. With the resurgence of AI, a new human-machine symbiosis is on the horizon. The question that remains is how humans and new Artificial Intelligences can be complementary in organizational decision-making.

To address this basic question, we draw upon the distinction between **analytical** and **intuitive** decision making, and the three challenges that plague decision making in organizations: **uncertainty**, **complexity**, **equivocality** (Choo, 1991; Simon, 1982). By studying the daily practices of managers and other organizational members, organizational scholars have distinguished between analytical and intuitive practices used in processing information and arriving at a decision (Dane, Rockmann, & Pratt, 2012). On the one hand, employing an analytical approach, individuals engage in methodical, laborious information gathering and analysis, developing 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 than intuitive decision-making. As noted, AI encompasses a broad range of applications and algorithms. However, in this article, we focus on analytical AI applications and techniques that imitate and extend the way humans reason, and therefore the way humans 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, they produce analysis, and they help evaluate alternative decision options.

On the other hand, 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 consider "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 with a holistic and abstract view of the problem. These two styles are not mutually exclusive, and are employed as parallel systems of decision making to more effectively address various contingencies.

Whilst 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 suggests, "Humans bring common sense to the work; by its definition, common sense is not a fact-based undertaking. It is a judgment call." (Captain, 2017). Therefore, humans tend to perform better in the face of decisions requiring an intuitive approach. In what follows, we present AI, embodying an analytical approach, as more effective in overcoming complexity in decision-making. Even though AI can offer some benefits in this area, addressing uncertainty and equivocality in decision-making will likely remain a comparative advantage for humans who can leverage superior intuition, imagination and creativity.

Uncertainty

Uncertainty is characterized as a lack of information about all the 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, and new government policies). AI and other intelligent technologies can generate fresh ideas through probabilistic and data-driven statistical inference approaches, and AI's unique affordances for identifying relationships among many factors can enable human decision makers to more effectively collect and act upon new sets of information. For example, one of the primary functions of predictive analytics is generating new information and predication about customers, assets and operations.

Consulting firms such as Deloitte and McKinsey have already developed some intelligent tools that offer monitoring and sensing of an organization's external environment, enabling semi-automated strategy articulation. As another example, AI systems can help managers detect anomalies by providing real-time insight about early warning signs of bigger issues, opening the possibility of timely corrective actions. Moore (2016) suggests 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.

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 epitomizes 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." (Sam, 2016). Problems ranging from global crises to technical glitches can result in unpredictable disruptions of 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).

Therefore, humans continue to excel in making decisions regarding real-world problems riddled with uncertainty. As a prominent example, when it comes to deciding on new products, Apple has rarely considered studies, surveys, or extensive research. It has also been rare 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." (Smith, 2016). 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', thereby shaping both the consumer technology market and customers' tastes. Steve jobs' 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 partly driven by tacit learning from previous mistakes and experimentations.

Beyond Apple, prioritizing intuition over analytical data is pervasive among senior decision makers. A top executive of one of the world's largest pharmaceutical companies described his approach as follows: "Very often people will do a brilliant job up through the middle-management levels where it's 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 big problem" (Hayashi, 2001)

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" (Parikh, 1994) is almost impossible to simulate with artificial intelligence. Machines tend to be 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, which require holistic and visionary thinking. This may be found in the more senior levels of organizations, since strategic planning activities may involve higher levels of ambiguity and uncertainty (Sadler-Smith & Shefy, 2004).

Complexity

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's contribution can range from assessing a person's credit risk by examining their friend list on Facebook, to pricing ads in digital marketing, to underwriting mortgages in the US 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 to continue to 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. One of the ways to materialize the synergic relationship between AI and humans is to combine the speed of AI in collecting and analyzing information with humans' superior intuitive judgement and insight. For example, Correlation Ventures, a venture capital firm that finances startups, assesses investment opportunities in two 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. As another example, 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). As remarked by Reid Hoffman, executive chairman of LinkedIn, 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)

Equivocality

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 and alliances). Even if machines can determine the most "optimal" decision, they are less likely to be able to sell it to a diverse set of stakeholders. Recall the example of chess. Murray Campbell, a key member of the IBM Deep Blue project, asserts: "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" (Campbell, 2016). 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 towards 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 and skills, and their delicate understanding of the social fabrics of their organizations (Cross, Borgatti, & Parker, 2002). Dissecting the labyrinth of complex social systems tends to lie outside the capacity of AI. Parry, Cohen, and Bhattacharya (2016) 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.

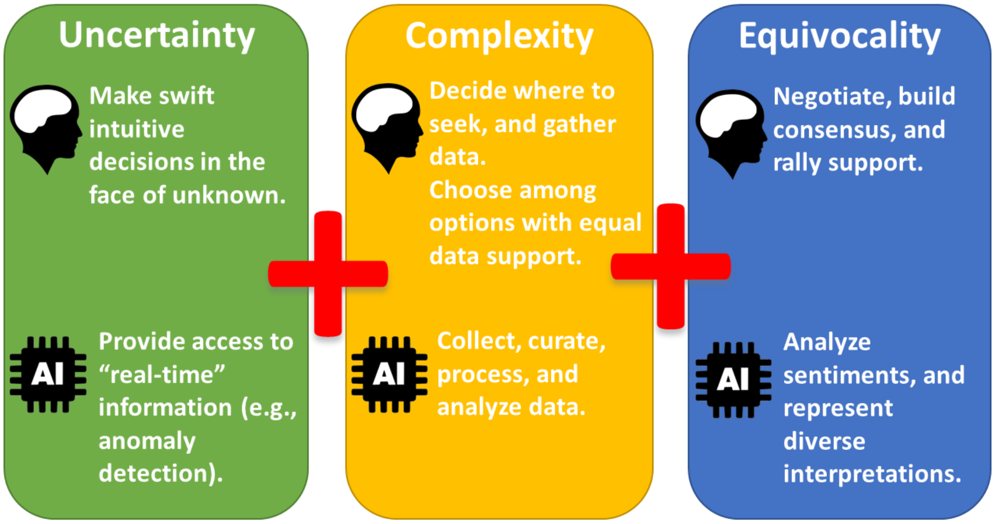
It is important to note that the decision-making process often involves all of these three characteristics (uncertainty, complexity and equivocality) (Koufteros, Vonderembse, & Jayaram, 2005), and these characteristics should not be understood as mutually exclusive. Most organizational decision-making is best handled by using a blend of both analytical and intuitive approaches (to varying degrees) (Hung, 2003). Martin (2009) puts 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) provides 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 inputs indispensable. For example, by bringing to bear intuitive approaches, humans can ascertain what variables or future events (out of endless factors) may more strongly influence outcomes, helping identify what factors must be foregrounded in data collection and analysis primarily undertaken by the analytically-based approach of smart technologies. Moreover, analysis in many cases may result in multiple alternate routes with almost equal factual supports; human 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) allowing humans to focus more on uncertainty and equivocality, using more creative and intuitive approaches.

2. As noted, even the most complex decisions, in which AI has a competitive edge, are likely to entail elements of uncertainty and equivocality. Therefore, as Figure 1 indicates, humans continue to play a role in almost all complex situations, as do AI in the face of uncertainty and equivocality.

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



Conclusions

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 partnership 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 directing attention to the comparative advantages held by humans and machines in relation to the three characteristics that beset almost all organizational decision making situations. Although AI capabilities help humans overcome complexity through the machines' superior analytical approach, the role of human decision makers and their intuition in dealing with uncertainty, and especially 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 which still offer humans unique positions in handling ambiguous and equivocal situations. Due to their intuitive capabilities, humans continue to perform better big-picture thinking. Davenport (2016) attests that broader strategic questions require a holistic approach, which cannot be captured by data alone. Henry Mintzberg (1994) presents 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" (p. 108). Cognitive technologies such as AI can certainly help, but strategic thinking in particular requires a level of sense making and understanding of the world beyond specific decision contexts that only humans are capable of. The likelihood of AI to learn, imitate and replicate the personal experience, sub-conscious thought patterns and personality traits of humans that drive superior intuitive decision-making is remote. Such an intuition in most cases is a nontransferable human attribute (Buchanan & O Connell, 2006).

It is not only upper management that engages in intuitive decision making in organizations. Many knowledge workers, even at the lower and non-managerial levels, constantly find themselves in novel situations (specifically characterized by uncertainty and equivocality), and therefore require visionary and intuitive thinking. Examples of these non-managerial 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, organization 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 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 argues (2012): "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" (Davenport, 2016), human intervention is arguably inevitable; therefore the possibility of having an exclusively AI-based organizational decision system is shortsighted.

Implications for managers and organizations

In AI-enabled business investments, the way many managers justify return on investment (ROI) in cognitive technologies typically centers on significant immediate headcount reduction (Davenport & Faccioli, 2017). Our premise in this paper 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 just 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

(Sawyer & Jarrahi, 2014), and technological breakthroughs prevail only if they are judiciously integrated into the social fabrics of an organization. AI is no exception.

Studies of previous technology-centered initiatives, such as business process reengineering, suggest that short-term financial gains from replacing humans can be ephemeral, and be 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 paper 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 exemplars. 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 on 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 possess the ability to 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, suggests smart bots helped teams of human players boost their performance (Shirado & Christakis, 2017). The technology aided the performance of teams by shortening the median time for human teams to solve problems by 55.6%.

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 competitive 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. Thus, 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 optimizing 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 or 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 AI.

References

Accenture. (2017). Technology vision 2017: Technology for people Retrieved 15 June, 2017 from https://www.accenture.com/t20170321T032507__w__/us-en/_acnmedia/Accenture/next-gen-4/tech-vision-2017/pdf/Accenture-TV17-Full.pdf?la=en

Bishop, P. (2000). *Synchronicity and intellectual intuition in Kant, Swedenborg, and Jung*: The Edwin Mellen Press.

Brynjolfsson, E., & McAfee, A. (2012). Winning the race with ever-smarter machines. *MIT Sloan Management Review, 53*(2), 53.

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

Buchanan, L., & O Connell, A. (2006). A brief history of decision making. *Harvard Business Review, 84*(1), 32.

Burke, L. A., & Miller, M. K. (1999). Taking the mystery out of intuitive decision making. *The Academy of Management Executive, 13*(4), 91-99.

Campbell, M. (2016). 20 Years Later, Humans Still No Match For Computers On The Chessboard. *NPR.* Retrieved, 10 June 2017 from http://www.npr.org/sections/alltechconsidered/2016/10/24/499162905/20-years-later-humans-still-no-match-for-computers-on-the-chessboard

Captain, S. (2017). Can IBM's Watson Do It All? *Fast Company.* Retrieved 2017, 10 Oct from https://www.fastcompany.com/3065339/can-ibms-watson-do-it-all

Choo, C. W. (1991). Towards an information model of organizations. *The Canadian Journal of Information Science, 16*(3), 32-62.

CIO Network. (2017). How AI And Machine Learning Are Helping Drive The GE Digital Transformation. *Forbes.* Retrieved 15 Oct, 2017 from https://www.forbes.com/sites/ciocentral/2017/06/07/how-ai-and-machine-learning-are-helping-drive-the-ge-digital-transformation/#31616fae1686

Cross, R., Borgatti, S. P., & Parker, A. (2002). Making invisible work visible: Using social network analysis to support strategic collaboration. *California management review, 44*(2), 25-46.
Dane, E., Rockmann, K. W., & Pratt, M. G. (2012). When should I trust my gut? Linking domain expertise to intuitive decision-making effectiveness. *Organizational Behavior and Human Decision Processes, 119*(2), 187-194.
Davenport, T. H. (2016). Rise of the Strategy Machines. *MIT Sloan Management Review, 58*(1), 29.
Davenport, T. H., & Bean, R. (2017). How P&G and American Express Are Approaching AI Thoma. *Harvard Business Review.* Retrieved 25 Sep, 2017 from https://hbr.org/2017/03/how-pg-and-american-express-are-approaching-ai
Davenport, T. H., & Faccioli, G. (2017). Cognitive on the Continent. *Data Informed.* Retrieved 2016, 10 Oct from http://data-informed.com/cognitive-on-the-continent/
Davenport, T. H., & Kirby, J. (2016). Just How Smart Are Smart Machines? *MIT Sloan Management Review, 57*(3), 21.
Frischmann, B., & Selinger, E. (2017). Robots have already taken over our work, but they're made of flesh and bone. *The Guardian.* Retrieved 10 Oct, 2017 from https://www.theguardian.com/commentisfree/2017/sep/25/robots-taken-over-work-jobs-economy?CMP=share_btn_tw
Gardner, W. L., & Martinko, M. J. (1996). Using the Myers-Briggs Type Indicator to study managers: A literature review and research agenda. *Journal of Management, 22*(1), 45-83.
Gray, M., & Suri, S. (2017). The Humans Working Behind the AI Curtain. *Harvard Business Review* Retrieved 1 Oct, 2017 from https://hbr.org/2017/01/the-humans-working-behind-the-ai-curtain
Guszcza, J., Lewis, H., & Evans-Greenwood, P. (2017). Cognitive collaboration: Why humans and computers think better together. *Deloitte University Press*.
Hayashi, A. M. (2001). When to trust your gut. *Harvard Business Review, 79*(2), 59-65.
Hoffman, R. (2016). Using Artificial Intelligence to Set Information Free *MIT Sloan Frontier, Fall 2016*.
Hung, S.-Y. (2003). Expert versus novice use of the executive support systems: an empirical study. *Information & Management, 40*(3), 177-189.
Kalev, L. (2016). Is Elon Musk Right And Will AI Replace Most Human Jobs? *Forbes.* Retrieved, 15 June 2017 from https://www.forbes.com/sites/kalevleetaru/2016/11/08/is-elon-musk-right-and-will-ai-replace-most-human-jobs/#2d1c95bb60f4
Kelly, K. (2012). Better than human: Why robots will—and must—take our jobs. *Wired*.
King, J. L., & Grudin, J. (2016). Will Computers Put Us Out of Work? *Computer, 49*(5), 82-85.
Koufteros, X., Vonderembse, M., & Jayaram, J. (2005). Internal and external integration for product development: the contingency effects of uncertainty, equivocality, and platform strategy. *Decision Sciences, 36*(1), 97-133.
MacCrory, F., Westerman, G., Alhammadi, Y., & Brynjolfsson, E. (2014). *Racing with and against the machine: changes in occupational skill composition in an era of rapid technological advance.* In Proceedings of the 35th International Conference on Information Systems. , Auckland, NZ.
Martin, R. L. (2009). *The design of business: Why design thinking is the next competitive advantage*: Harvard Business Press.
Marwala, T. (2015). *Causality, correlation and artificial intelligence for rational decision making*. Singapore: World Scientific.
Mintzberg, H. (1994). The fall and rise of strategic planning. *Harvard Business Review, 72*(1), 107-114.
Moore, A. W. (2016). Predicting a Future Where the Future Is Routinely Predicted. *MIT Sloan Management Review, 58*(1), 18.
Mumford, E. (1994). New treatments or old remedies: is business process reengineering really socio-technical design? *The Journal of Strategic Information Systems, 3*(4), 313-326.

New Vantage Partners. (2017). *Big Data Executive Survey 2017*. Retrieved from http://newvantage.com/wp-content/uploads/2017/01/Big-Data-Executive-Survey-2017-Executive-Summary.pdf
Parikh, J. (1994). *Intuition: The new frontier of management*. Oxford: Blackwell Business.
Parry, K., Cohen, M., & Bhattacharya, S. (2016). Rise of the Machines: A Critical Consideration of Automated Leadership Decision Making in Organizations. *Group & Organization Management, 41*(5), 571-594.
Russell, S., Norvig, P., & Intelligence, A. (1995). *Artificial Intelligence: A modern approach*. Egnlewood Cliffs: Prentice-Hall.
Sadler-Smith, E., & Shefy, E. (2004). The intuitive executive: Understanding and applying 'gut feel'in decision-making. *The Academy of Management Executive, 18*(4), 76-91.
Sam, R. (2016). Can Artificial Intelligence Replace Executive Decision Making. *MIT Sloan Management Review, June 28*.
Sawyer, S., & Jarrahi, M. H. (2014). Sociotechnical Approaches to the Study of Information Systems. In A. Tucker & H. Topi (Eds.), *Computing Handbook, Third Edition: Information Systems and Information Technology* (pp. 5.1-5.27).). Boca Raton, FL: Chapman and Hall/CRC.
Shirado, H., & Christakis, N. A. (2017). Locally noisy autonomous agents improve global human coordination in network experiments. *Nature, 545*(7654), 18.
Simon, H. A. (1965). *The Shape of Automation for Men and Management*. New York: Harper and Row.
Simon, H. A. (1982). Theories of bounded rationality. In H. A. Simon (Ed.), *Models of bounded rationality. Behavioral economics and business organization* (Vol. 1, pp. 408-423). Cambridge, MA: MIT Press.
Wang, D., Khosla, A., Gargeya, R., Irshad, H., & Beck, A. H. (2016). Deep learning for identifying metastatic breast cancer. *arXiv preprint arXiv:1606.05718*.
Weick, K. E., & Roberts, K. H. (1993). Collective mind in organizations: Heedful interrelating on flight decks. *Administrative science quarterly*, 357-381.
Wladawsky-Berger, I. (2017). The Emerging, Unpredictable Age of AI. *MIT Initiative on the Digital Economy.* Retrieved 1 Oct, 2017 from http://ide.mit.edu/news-blog/blog/emerging-unpredictable-age-ai
Zuboff, S. (1988). *In the age of the smart machine: The future of work and power*: Basic books.