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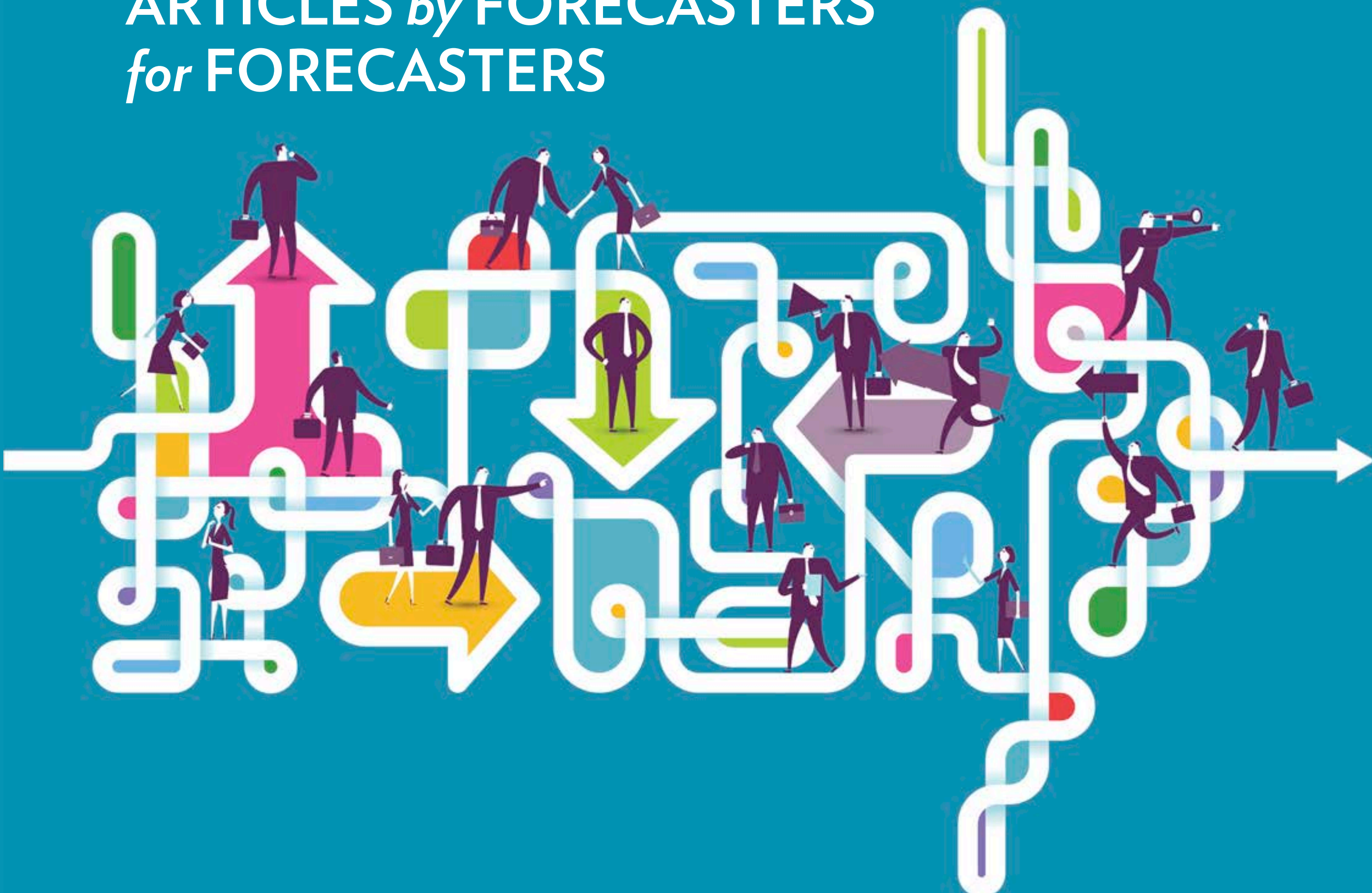


Combining Humans and Machines in an Emerging Form of Enterprise: the Humachine

NADA SANDERS AND JOHN WOOD

PREVIEW *Nada Sanders and John Wood, authors of* The Humachine*, believe that business leaders would be wise to resist the temptation to replace traditional business processes entirely with artificial intelligence (AI). Instead, they propose that a synthesis of human and machine will provide benefits beyond those achieved by humans or machines alone.*

INTRODUCTION: LINKING HUMAN AND MACHINE INTELLIGENCE

Research shows that over one third of companies are taking a passive approach to AI, looking at the field from the sidelines and studying the competition. Others believe that using algorithmic-based automation is all that is needed to be competitive (Ransbotham and colleagues, 2018).

Business leaders can be forgiven for thinking that competing in the age of AI is about implementing machine intelligence to displace human workers. In a recent *HBR* article, Marco Iansiti and Karim Lakhani (2020) claim that, "Rather than relying on traditional business processes operated by workers, managers, process engineers, supervisors, or customer services representatives, the value we get is served up by algorithms." (p. 62)

We contend this view may be shortsighted, mistakenly characterizing the emerging green shoots of AI for the fruit itself. Rather than viewing AI as the main source of value creation, we consider it to be an intermediate step, a necessary condition for achieving competitive advantage but not sufficient in itself.

Integrating AI into Operations

This is the caveat to the hype around AI. The popular press is inundated with examples of business innovation characterized by machine learning (ML), robotic process automation, digital networks, and the Internet of Things (IoT), triggering that powerful fear of missing out while also raising the cost of trying to keep up with the hype. As Khari Johnson (2020) recently noted, "Business executives are rushing to implement the technology into their operations and gain a competitive advantage, but it's not as simple as creating a data lake and crafting AI models."

Technologies associated with AI—autonomous devices, ML algorithms, neural nets, and more—are being built on digital infrastructures from Customer Relationship Management (CRM) platforms to IoT-connected systems. The emergence of these technologies has shifted the competitive landscape decisively in favor of companies that are seeking to stack AI capabilities atop a digital platform. While there is little or no question that AI is introducing revolutionary impacts to operations, strategy, and competition, it does not fit the plug-and-play model of technology adaptation that has driven innovation over the last several decades. Integrating AI into a firm's strategy is not like updating workforce laptops or installing a new CRM platform: it is unlike any technological change that has ever occurred in recorded human history.

Despite the surge of interest in adopting the latest "smart" technology, it would be a mistake to look at AI as yet another incremental technological investment like the latest personal computer. Competing in the age of AI is not about acquiring better technology per se. It's about properly integrating technology with human resources to leverage the virtues of each while avoiding their limitations. The future will belong to those companies that are implementing AI at the enterprise level, mutating into a new form of enterprise entirely—not one that simply jettisons the human workforce and replaces them with algorithms, but rather one that combines the highest capabilities that humankind has to offer with the newfound and continually emerging powers of AI. Companies that mistakenly treat AI as another piece of technology to tack on to their company will go the way of Blockbuster Video.

Rethinking the Enterprise

The reason old business models will not succeed in the age of AI is that what is needed of the human element at all levels of the organization is dramatically changing. This requires a new way of thinking about the role of humans in an enterprise while rethinking the enterprise itself. There are already a number of leading companies, such as Google and Haier, that are changing the boundaries and activities of their firms. They are redefining processes, functions, and their interactions, representing a paradigm shift in business models.

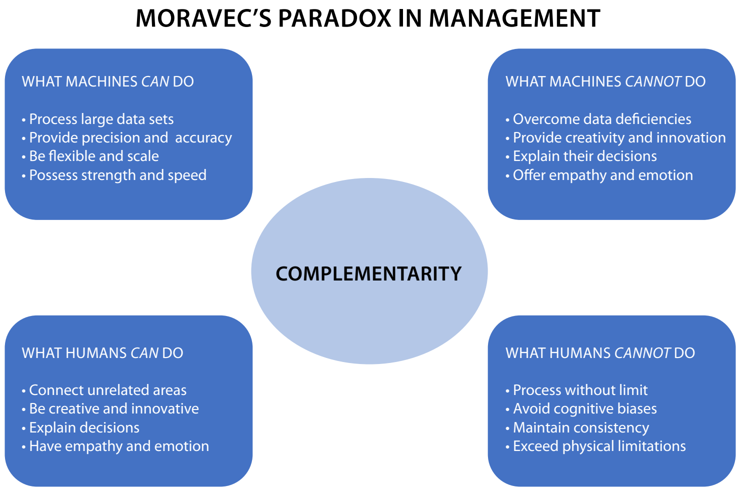
Adopting the latest AI technology is without doubt important, and most companies have been hesitant to fully embrace "digital transformation." While there has long been a carrot to adopt technology to gain competitive advantage, the COVID-19 pandemic has become a stick, forcing leaders to lean on technology without the needed runway to fully understand the organizational transformation required for successful implementation. The belief that competing in the age of AI is about acquiring "smart" technologies like in-store sensors is an outdated paradigm. It didn't work before the pandemic when many brick-and-mortar retailers were already beginning to slide into bankruptcy. And it's not enough now.

Using algorithms instead of traditional business processes is merely the order qualifier, not the order winner. Human integration with technology is the key to thriving in the age of AI; it can unlock organizational network superintelligence, resulting in a type of enterprise we call the humachine, one that vastly outperforms any competing company governed by mere human intelligence. It is an enterprise that creates synergies between human talent and AI, where the whole is far greater than the sum of the parts.

Key Points

- While humans may never attain machinelike capabilities, Moravec's Paradox (where humans are naturally gifted, machines struggle, and where machines excel, humans find difficulty) asserts that certain human skills are virtually impossible to replace with automation. Instead of "botsourcing" human capital, business leaders should follow Kasparov's Law, which documents that superior performance can be achieved by combining humans and machines.
- Our research leads us to forecast the emergence of a new form of enterprise that harnesses the strengths of humans and machines in a symbiotic relationship, which can achieve a "superintelligence" that outstrips performance achieved by either humans or machines alone.
- We call this enterprise form the *humachine*—and it is not science fiction. A number of leading firms are already exhibiting traits of the humachine, which we explain here.
- In this new enterprise form, organizational functions are fundamentally different, but few are impacted as much as the forecasting function. The humachine uses a forecasting process that optimizes the combination of human judgment and statistical forecasts generated via algorithms.
- Although a great deal of research has already been done to identify the mechanisms for combining human judgment with statistical methods, the age of AI offers new uncertainties, different types of models, and an unprecedented amount of data, all of which enable new thinking on the optimal manner of combining statistical and judgmental forecasts.

Figure 1. Complementary Strengths of Humans and Machines



The Survey

We conducted a survey of senior managers and executives over a five-year period, as well as performing in-depth studies of four leading organizations. Our objective was to identify how companies use AI technology and what traits are key to successful leadership.

We found that these leading firms differ in many aspects beyond technology. We were then able to identify that it is the integration of humans and technology within the enterprise that is most important, allowing us to coin the term "humachine" and identify the characteristics of this new form of enterprise.

We found that what differentiates the leading companies in the age of AI is actually a business model with a greater focus on acquiring and accommodating talent, rather than a sole focus on technology. Further proof comes from Kasparov's Law, which shows that the combination of ordinary humans and ordinary machines using the right process leads to superior performance. Kasparov's Law leverages the innate strengths of humans and machines, recognized by AI and robotics researchers and known as Moravec's Paradox.

WHY HUMACHINE WORKS: MORAVEC'S PARADOX

We are in an age of infatuation with evolving technological capability. However, it is still humans—executives, managers, and other decision makers—who use the output of algorithms to make decisions within an organizational context. These decision makers bring their human judgment, individual personalities, opinions, and expertise to the process, deciding how to use the analytically generated output. Even UPS truck drivers are authorized to override the route-optimization algorithm.

Some forecasts suggest up to 25% of the U.S. labor force will be displaced by automation by 2030 (Harris and colleagues, 2017). Humans and technology are increasingly viewed as competitors for jobs. We see this as a failure to think creatively about the future. When the steam engine came along, people who worked in horse stables may have panicked over job losses, too. For each previously human job description lost to robotic process automation—we call this phenomenon "*botsourcing*"—there could be several new jobs created involving co-bots, robot interpreters and human handlers.

Humans and machines have a paradoxical relationship, described by *Moravec's Paradox*: where humans are naturally gifted, machines struggle, and where machines excel, humans find difficulty (Moravec, 1988). This relationship between humans and machines is complementary, as shown in **Figure 1**. For example, while AI can now do many mental tasks that require "thinking" (such as mathematics), AI has a hard time doing what biological beings easily do without thinking (such as navigating a dynamic physical environment).

Machines are just tools. They cannot fix bad processes, poor management practices, or failing employee morale. It takes the human touch to do that. Moravec's Paradox is why companies cannot simply botsource their way to success. We can't take humans out of the equation. Even today, in a world dominated by technology, the key to success is to adapt humans to this new work environment—not to replace, but to enhance, not to train humans to think like computers, but to think *with* computers.

This human-centric approach of technology-focused firms is exemplified by the likes of Google and Haier. These companies understand that they must transform the way they do business to remain competitive. It is not about changing technologies to get the latest and greatest systems, but rather changing the business model itself. The issue is not how to replace humans with free robot labor—which myopically accounts for human resources as a cost instead of an asset. The issue is how to create a business model where machines and humans complement each other, unlocking the highest potential value of each. Machines will do repetitive and automated tasks. They will even do complex cognitive tasks and make semiautomated movements. However, those uniquely human skills of creativity, innovation, adaptability, empathy, integrity, playfulness, emotional intelligence, care, and imagination will become increasingly imperative to success.

We doubt that AI will ever attain the general intelligence needed to exemplify those uniquely human skills, at least not on relevant time horizons for corporate leaders to seriously consider turning over the reins of a company to AI. It is precisely these human skills that are needed to bridge the gap between technology and people and utilize machines in the best way to serve people—customers, coworkers, suppliers, and all other stakeholders. Leading AI companies know this and focus more on building work systems to fit human ergonomics rather than training humans to fit the demands of work. Indeed, there is proof that this works. Kasparov's Law proves that we do not need the greatest technology—or even the smartest people—to achieve superior performance. We need the best process of human-machine integration.

USING AI TO PLAY TO OUR STRENGTHS: KASPAROV'S LAW

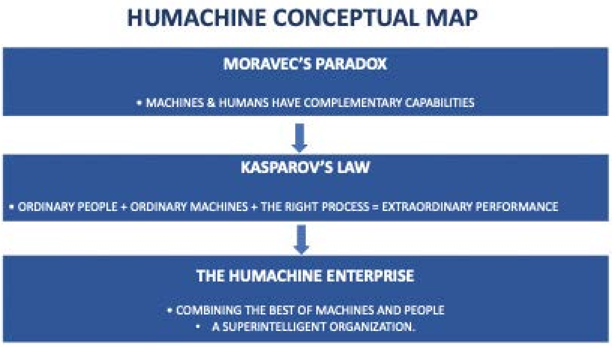
In 1997 the stakes were high when then-greatest-of-all-time chess champion Garry Kasparov was defeated by IBM's Deep Blue chess-playing computer engine. The loss to Deep Blue sent shockwaves through the competitive chess community and all the computer scientists following the advances of IBM's computing innovations. This was the first time Kasparov had ever lost a chess match and his first loss ever was to a machine. ***https://open.spotify.com/episode/6JRpPEFhkd9qNjUAwxmYCS?si=y0tHC4ZYRd2V3U2JfD8BIQ***

The loss put him in a reflective mood and drove him to stage an experiment to test whether humans can attain mastery to beat machines (Kasparov, 2017). He designed the Ultimate Chess Tournament to function as an experiment. Prevailing in a chess tournament could perhaps be considered a stand-in to test the superiority of the intellects competing therein, at least to the limited extent that chess is a valid test of intelligence. It seems intuitive to use chess in this manner. Playing requires logical reasoning and tests the strength of the player's ability to reason through implications, to entertain and evaluate counterfactual scenarios, and to pursue tactics that are rational in decision making under constraints in a competitive environment. Unlike standard chess tournaments, Kasparov designed the tournament entry rules to allow multiple chess players per team and allowed for teams of chess players to also use computer programs. The tournament drew world-class chess engines and grand-master chess players as competitors—and the outcome was surprising.

Neither the smartest computer algorithms nor the most accomplished chess players won the Ultimate Chess Tournament. Rather, the championship went to a team of two amateur chess players who were virtual unknowns in the competitive chess-playing world. Using a custom homegrown computer algorithm that they trained on data from prior games, they learned which of the two of them tended to make better moves, depending on how the board was arranged. The algorithm would let the humans play to their strengths.

The key to victory was *a better decision-making process*, one that used deep analysis by the algorithm to tap into the best

Figure 2.



judgment of the human players—a simple yet elegant way of leveraging Moravec's Paradox. The fact that the amateurs prevailed in this experiment is just one result, but it may have proven *Kasparov's Law*—that the combination of ordinary humans and ordinary machines using the right process can lead to superior performance, even triumphing over human genius or powerful computers alone. Following Kasparov's Law, we can build organizations of superior intelligence, using ordinary human resources and clever algorithms—no geniuses or supercomputers needed. **Figure 2** shows a conceptual map of this development. Moravec's Paradox offers the foundation for Kasparov's Law, and the latter offers proof of the success of the human and machine partnership.

We believe that in the age of AI, using algorithms will help gather up the low-hanging fruit. However, eventually these technologies will be standard practice across all industries. Using algorithms instead of traditional business practices will no longer provide a competitive advantage once the transition into the age of AI has permeated the market. That will take a new form of enterprise—a superintelligent enterprise. As described next, achieving organizational network superintelligence is the strategy that we believe will provide a dominant competitive position for companies in the age of AI.

ATTAINING SUPERINTELLIGENCE

We use "superintelligence" as the term is defined by Nick Bostrom, Oxford University professor, founder of the Future of Humanity Institute, and author of *Superintelligence: Paths, Dangers, Strategies* (2020). Superintelligence is a form of intelligence that vastly outstrips human cognitive performance across all relevant domains of interest. Bostrom persuasively argues that creating superintelligence is the biggest challenge humanity will ever face. Suffice it to say this concept is relevant for business leaders eager for their organizations to remain competitive in the long run.

Bostrom outlines several distinct pathways that might lead researchers to creating superintelligence, including biological cognitive enhancement, whole-brain emulation, neural lace, and collective superintelligence. While these pathways may be thought provoking, our research shows only the latter pathway is realistically feasible in the immediate term and is attainable by business leaders. Neural lace, for example, requires implanting electrodes into the human skull and we certainly don't know any business leader eager to succumb to that procedure. Collective superintelligence, however, is immediately attainable, and we call this "organizational network superintelligence." According to Bostrom, this kind of superintelligence is not only possible, but would emerge "through the gradual enhancement of networks and organizations that link individual human minds with one another and with various artifacts and bots," (p.58-59) saturated with big data, and organized around the principles we outline here.

Although superintelligence sounds like a futuristic concept, this pathway is not dependent upon a breakthrough in technology. Companies can create superintelligence in an enterprise using the human and technological resources available by developing human-centric processes through an entirely different business model, combining the three variables of Kasparov's Law needed to create superhuman capabilities: *people*, *machines*, and *processes*. "People" includes everyone from company leaders and coaches to analysts and designers, as well as customers and suppliers. Machines are the technologies from AI and IoT, to platforms, network links, and cloud computing. There are a number of features we observed that are common to these organizations, as we next discuss.

HUMACHINE TRAITS

Companies such as Google and Haier exemplify features of the humachine business model we have observed in a number of other companies. The success of these companies comes not only from better technology but because they have transformed the way they do business so that human resources can be augmented with machine powers. The secret is the business model itself, where machines and humans are integrated in a process designed to complement each other as noted by Kasparov's Law. Success comes from harnessing this combined power of technology and human resources.

The list of features is outlined in **Figure 3**. The first feature is selection of *technology that supports human needs*. Organizational goals are outlined and technology is chosen targeted to support those goals, not just following the latest technological advancements. Second, the humachine business model is driven by a *shared vision and purpose* that ties humans to the organization. Humans are emotional and thrive on meaningful relationships in an organization that has a greater purpose. Research shows that organizations can get the best out of their talent by leveraging these emotions. Having a purpose in society beyond mere profit capture is a critical element of success. It is hard to inspire innovation, creativity, and engagement with purely a profit motive, and this will not suffice in an era where greater human capabilities are needed.

Another observed feature is *flexible organizational structures*. Agility and flexibility are increasingly required as machines and humans work to adapt in real time to customer and environmental demands. This requires a shift from rigid functional procedures to systems thinking; away from silos and rigid hierarchies to cross-functional integrated

Figure 3.

HUMACHINE TRAITS

- Technology supporting human needs
- Technology adopted to support a shared vision
- Meaningful relationships
- Flexible organizational structures
- Integrated work teams
- Combined physical and virtual work environments
- Aspirational and measurable metrics

teams and flatter organizations. The key is to play to individual strengths, responding and communicating with one another in real time and fostering innovation and adaptability.

At Google, structure and culture interact to influence the capabilities of the organization as one unit. Innovation is at the heart of Google culture, and Google uses a matrix organizational structure enabling cross-functional groups to work across traditional vertical silos. The same is true with Haier, where cross-functional teams are formed as needed, then dissolved and reformed as a new need arises. While each of these companies has its own unique organizational structure, the common elements are a flat structure that enables flexibility and rapid response to changing environments.

Lastly, we find that humachine companies combine the best of the *physical* and *virtual environments*, focusing on *metrics that motivate performance and innovation*. Workers are flexible to move from one work environment to the other with a focus on performance and results.

To take advantage of a flexible structure, a company needs a culture of freedom to create and innovate, regardless of where workers are located. Haier, for example, pushes entrepreneurship and innovation, recognizing that the digital era has reshaped customer expectations and that as a company it has to disrupt the status quo. To this end, Haier created an organizational structure and culture that is extremely responsive to customer needs, constantly cultivating new ideas and innovating quickly. Haier has turned itself into several microenterprises and the focus is on performance outcomes, not micromanagement. The idea is to turn Haier employees into micro-entrepreneurs who run their own microenterprises centered around an innovative idea or a product. They are responsible for their own performance, budgets, profit and loss, and will behave as independent business units under the Haier umbrella. Technology is used to support workers in their endeavors.

Collectively these traits form an enterprise that is not centered on technology but rather uses technology to support the organizational strategy and is integrated with the human workforce. The humachine has a shared vision, fluid and flexible structures, a culture that allows risk taking, innovation and creativity, and a technology that supports human needs.

IMPACT ON THE FORECASTING PROCESS

In this new enterprise form, organizational functions are fundamentally different, but few are impacted as much as the forecasting function. The humachine uses a forecasting process that optimizes the combination of human judgment and statistical forecasts generated via algorithms.

Forecasters have expressed various preferences for the use of human judgmental versus statistical methods. Some feel that judgment should not be given credibility due to high subjectivity. Others point to the restrictions of human cognitive abilities such as limited processing ability, short-term memory, overconfidence bias, and difficulties in understanding functional forms.

On the other hand, we have forecasters who support the use of judgment in forecasting, and we know that practitioners rely heavily on judgmental forecasting methods. The primary reason for this practice is that judgment is privy to the latest information on markets, competition, and changes in the environment, called "soft" information. For example, marketing may become aware of rumors of a competitor launching a promotion, a planned consolidation between competitors, or a sudden shift in consumer preferences due to changes in technology. Other information may be causal in nature, such as the relationship between sales of snow shovels and snowfall, or temperature and ice cream sales. There are few better examples than the surge in sales of hand sanitizer during the pandemic, which historical data could not have predicted.

Statistical methods have the advantage of being objective, consistent, capable of processing large amounts of data, and considering relationships between numerous variables. However, statistical models are only as good as the data upon which they are based. When changes occur in the data that are not incorporated in the model, the forecasts cannot be accurate. Even with all the AI capability, it was impossible to predict the onset, magnitude, and duration of the pandemic.

In the COVID era, rather, the process of forecasting has been a combination of human judgment—in this case, epidemiologists and physicians—with mathematical algorithms that forecast propagation of disease under various scenarios. The flat and fluid organizational structures in a humachine allow constant communication across functions and sharing of information, from marketing to operations and sourcing. This enables pooling of soft information with stable, quantitatively derived data. Consider that prior to the 2020 holiday season, the CFO of Walmart said the company's executives were judgmentally adjusting their analytics algorithms for quantities of food items to stock. Why? The reason was the acknowledgment that algorithms were based on historical data and the COVID-19 pandemic had created very different consumer behavior expectations. The algorithms could serve as a baseline. However, it was up to executives—knowing what was happening in the environment—to add their judgment to the final forecast.

Following Moravec's Paradox, the ideal forecasting methodology is one that incorporates the advantages of both human judgment and statistical forecasting and is something we are witnessing in humachine organizations. How precisely to do this is an evolving question, which provides a tremendous opportunity and need for researchers to identify the best conditions for using judgment, when to rely exclusively on statistical models, and when and how to combine them. Although a great deal of research has already been done to identify the mechanisms for combining human judgment with statistical methods, the age of AI offers new uncertainties, different types of models, and an unprecedented amount of data. This is an important opportunity for researchers to delve into, rethinking the best approaches to combine judgmental and statistical methods and offer guidance to this emerging enterprise form.

CONCLUSION

We set out on a journey to identify the transformative power of technology, only to discover that the key to corporate success rests with human talent and the firm's ability to integrate it with technology in a symbiotic way. Kasparov's Law tells us that the right combination of ordinary humans and ordinary machines can yield superior performance, even outcompeting human genius and specialized computers. For an enterprise to succeed in the age of AI, it must break free from old business paradigms and embrace a human-centric business model that actively leverages human strengths. It is the human-centric AI strategy that can lead to a superintelligent organization that outperforms firms governed by human intelligence alone, and which enjoys a sustainable competitive advantage by getting the most out of humans and machines.

REFERENCES

Bostrom, N. (2014). *Superintelligence: Paths, Dangers, Strategies*, Oxford University Press, Oxford, UK, 2014.

Harris, K., Kimson, A. & Schwedel, A. (2018). *Labor 2030: The Collision of Demographics, Automation and Inequality*, Bain & Co., February 7. Available at **https://www.bain.com/insights/labor-2030-the-collision-of-demographics-automation-and-inequality/**

Iansiti, M. & Lakhani, K (2020), Competing in the Age of AI: How Machine Intelligence Changes the Rules of Business, *Harvard Business Review* (January-February), 62.

Johnson, K. (2020). World Economic Forum Launches Toolkit to Help Corporate Boards Build AI-First Companies, January 17, Available at **https://venturebeat.com/2020/01/17/world-economic-forum-launches-toolkit-to-help-corporate-boards-build-ai-first-companies/**

Kasparov, G. (2017). *Deep Thinking: Where Machine Intelligence Ends and Human Creativity Begins*, Hatchet Books, 246.

Moravec, H. (1988). *Mind Children: The Future of Robot and Human Intelligence*, Harvard University Press.

Ransbotham, S., Gerbert, P., Reeves, M., Kiron, D. & Spira, M. (2018). Artificial Intelligence in Business Gets Real, *MIT Sloan Management Review* and The Boston Consulting Group, September.

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Commentary: AI Is Here to Automate the Knowledge Worker

NIELS VAN HOVE

INTRODUCTION: A NEW ERA

The authors of *The Humachine* make a valid point that enterprises should not focus on artificial intelligence (AI) alone if they wish to leap forward in automation, productivity, and competitiveness while staying relevant for attracting talent. They elegantly position Kasparov's Law (the combination of ordinary humans and ordinary machines using the right processes can lead to superior performance, even triumphing over human genius or powerful computers alone) as an addition to any future operating model in enterprises incorporating AI.

An operating model describes how an enterprise delivers value to its customers. It connects strategic directions with operational executing and stays with the vision, values, and behaviour framework for a business. The model contains, but is not limited to, organisational design, people and capabilities, roles and responsibilities, business processes and interactions, KPIs, reward and recognition, technology usage, governance and reporting. Many of these elements will be affected by AI and Kasparov's Law.

We are entering an era where we change from people doing the work supported by machines to machines doing the work guided by people. The interaction between human and machine will become critical in any future operating model.

AI TO AUTOMATE DECISIONS OF THE KNOWLEDGE WORKER

The authors correctly consider AI to be the centre of value creation in the future enterprise. However, they don't specify what AI will do. In my view, it is simple: AI is here to automate the knowledge worker.

Automation has been happening for hundreds of years. It has long been focused on improving productivity of boring, repetitive, or dangerous human activities. We now have automated production facilities, warehouses, and transport in our physical supply chain. With robotic process automation (RPA), it entered the back office to simplify repetitive tasks like invoice matching or purchase-order creation and acceptance.

The next step through AI is to automate the knowledge worker, either supporting or automating their cognitive tasks. It will help the knowledge worker make decisions and act if required. AI will enable cognitive automation.

AI algorithms will gather, analyse, and interpret data, and make decisions and execute them. It will do so at a higher speed, larger scale, greater consistency and precision, and with more endurance than any human is ever capable of. It might first augment decisions of a knowledge worker in medicine. I know a surgeon who uses AI-driven pattern recognition as a second opinion before he decides to remove a polyp. Take this one step further and AI cuts out the polyp by itself.

Similarly, AI-driven decision augmentation and automation is fast becoming a reality for the knowledge worker in the enterprise. However, there are limits to how far it can go.

FOCUS OF HUMAN AND AI INTERACTION IN DECISION MAKING

In my *Foresight* article "Technology Support in Decision Making" (2020), I described six drivers of whether AI will augment or automate decisions: data generation, decision granularity, frequency, complexity, impact, and human centricity. I argued that as the decision horizon lengthens from operational through planning to strategic, automation decreases and human centricity increases.

This logic can be combined with the authors' observation, through Moravec's Paradox, that machines and humans have complementary strengths. These must be understood when deciding when machines should be the lead for decisions, when humans should be the lead, and when to require collaboration between them.

I differentiate at least four types of decision making:

Operational During execution and the short-term operational horizon, business decisions are highly frequent, repetitive, and at a low granularity level with mostly small impact. These decisions can be highly automated. Think about a production line, stock movements in a supply chain, and the Amazon policy of changing prices of its millions of products automatically. In the humachine, AI is leading here and only guided by humans.

Planning Planning decisions beyond the operational horizon are less frequent, with higher granularity level, higher impact, and with often more complexity. There is decision time for the human to be *augmented* by AI while the cost of automating a decision might be excessive. The humachine needs to be highly collaborative in order to evaluate what-if scenarios, risk modeling, and probable outcomes suggested by AI to be decided by humans. This is where Kasparov's Law is most impactful.

Strategic Strategic decision making is infrequent, at a high granularity level, with a high impact and complexity of relationships and interconnectivities. Examples would be the decision to enter a new market or engage in a merger. In the humachine, the human will lead and act while AI provides some augmentation, but no automation.

Cultural Any business decision that involves values, behaviours, ethics, or virtues needs to be human centric. Defining who you want to be as a business, or understanding the social or cultural aspects of decisions, can only be done when the human is leading in the humachine.

KEY ELEMENTS FOR INTEGRATION OF AI INTO AN OPERATING MODEL

To start the journey towards the humachine and integrate AI in the operating model, a company will have to consider at least the following four elements, in a seamlessly integrated fashion:

Dynamic Data It all starts with data—the petroleum of the 21st century—and AI algorithms are data hungry. Without data you cannot extract value from AI. If you do not own the data in your value chain, it must be purchased or otherwise acquired. *Digital natives*, companies that have built their enterprise around data, have an early advantage; think Netflix and Amazon.

The nondigital native enterprise will have to catch up, requiring connections to dozens or hundreds of internal legacy systems as well as dozens of external sources, maybe even thousands in the case of IoT connections. The data model needs a read capability to feed up-to-date information to the algorithms and write-back capability to underlying legacy systems. A static data lake will not suffice anymore. As I heard a Chief Technology Officer mention: "Data lakes that are not dynamic and can't operationalize in day-to-day business become data graveyards."

Transparent Science Companies with advanced analytics and AI capabilities tend to employ groups of data scientists working apart from the rest of the organization, possibly for months at a time, before presenting results to stakeholders. Their algorithms need to be transparent, a glass box. Subject-matter experts in any function need to be able to interact with algorithms, change them, tune them, and operationalize them in a user-friendly way.

Most companies do not need to own algorithms as intellectual property or trade secrets. There are open-source AI algorithm libraries and languages like R and Python.

Digitised Processes Kasparov's Law requires a process that works effectively between human and machine. In future operating models, the process will be mostly digitized. We already see the rise of the "digital twin," the automated process that exactly copies the steps from a human to analyze, decide, and act, whatever the functional area is.

Companies must be able to digitize their processes, a vital prerequisite for any operating model that has AI at its core.

ORGANIZATIONAL CHANGES

In order to enable the humachine and nurture Kasparov's Law, an enterprise will have to rethink several change elements.

1. Machine-to-human interaction
How will the machine present advice to the human? Will there be an easy-to-understand user interface? And how does the machine inform the human of decisions that have been automated without human involvement? These policies need to be transparent, not a black box.

2. Human-to-machine interaction
How will the human provide input and guidance to the machine? People will have to instruct the machine during setup and periodically examine the machine's decision logs to check and possibly correct alignment with corporate values and strategic goals.

3. Organizational change
How will the enterprise support the humachine? Will the organizational design adapt as fewer humans are charged with increased scope of responsibility? How will recognition and rewards to employees be adjusted to promote collaboration with machines and excellence at human-centric capabilities?

Sanders and Wood are right that a shared vision and purpose is prerequisite to embrace the change needed to transform to the humachine. Digital natives, whose culture is already data centric and AI collaborative, again have a natural advantage.

Nondigital natives must drive this new culture from the top down. This is already happening. The CEO of Unilever, a 90-year-old CPG giant with 2.5 billion daily customers, 161,000 employees, and 300 production facilities across 190 countries, has put digital transformation at the heart of its strategy. Marc Engel, its Chief Supply-Chain Officer, has publicly declared that investing in agility, which he defines as quickly sensing change and responding to it, gives in his opinion a 10X return versus investing in forecasting and scenario planning. As a nondigital native, Unilever is becoming a global leader in cognitive automation (***https://www.supplychaindive.com/news/unilever-csco-agility-forecasting-coronavirus/581323/***).

While the right corporate culture can help, much is also dependent on the individual mindset of the employee. One can look at Garry Kasparov for inspiration: he is a highly motivated and extremely competitive individual. Although the world's best at what he does, he lost to a machine while the world watched and then proclaimed to be the first knowledge worker put out of a job by a machine. But, with some hesitance, he took an interest in AI and the value it can bring when the machine is working together with the human. He opined that the humachine is the best way forward for increased performance, first for chess, then for the wider world and business.

We need individual mindsets like this if the transition to the humachine is to happen. Knowledge workers should take notice.

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Commentary: ML Must Be Used with Care

DAVID ORRELL

Nada Sanders and John Wood argue that a merger of human and machine can lead to what the philosopher Nick Bostrom, head of Oxford's Future of Humanity Institute, calls "superintelligence"—intelligence that can outperform either humans or machines acting alone.

As the authors note, machine-learning algorithms, at least in their current form, excel at certain kinds of problems but do less well at others. It is one thing to comb through countless strategies to produce a winning move in chess or go but another, it seems, to nail the perfect movie recommendation (an early adopter of machine learning, of course, being Netflix).

In finance, machine learning has been used by hedge funds since the late 1980s. One popular ML approach is to look at investor sentiment, measured by things like hashtags on Twitter. The limitations of such approaches are revealed by the Eurekahedge AI Hedge Fund Index—which uses ML to track the returns of 13 hedge funds—shown to have had an average annual return for the past five years of 5.5 percent, as compared to 12.5 percent for the S&P 500.

In health care, where data analytics is playing an increasingly important role, ML algorithms also can be frustrated by the noisy nature of the data, to the point where there are few rigorous studies that demonstrate superiority over expert-based methods (Mistry and Orrell, 2020). Their bias in areas such as recruitment is well documented. It seems that computers are highly efficient at finding patterns in anything from CVs to hospital visiting-time data, but are less good at assessing whether they are relevant or meaningful. ML algorithms therefore do well at analysing closed games with well-defined rules, such as chess, but must be used with care when it comes to complex real-world problems.

On the other hand, humans aren't perfect either.

The Integration Problem

As Sanders and Wood point out, the problem is how to correctly integrate humans and machines to work together in synergy, and they give many useful pointers on how this can be done.

An additional example is the MSI Brain system of Mitsui Sumitomo Insurance, which they describe as "a fusion of human and artificial intelligence, combining customer relationship management with sales force automation. The agent is able to uncover the customer's potential needs through analysis of massive amounts of data, with MSI Brain then suggesting what insurance products to propose and in what way." The aim is to "create a sustainable system in which AI and people grow together" (Funabiki, 2021).

Such hybrid systems may even play a role in geopolitics. As former NORAD chief Terrance O'Shaughnessy wrote of the artificial-intelligence program known as Strategic Homeland Integrated Ecosystem for Layered Defense (SHIELD), it "pools this data and fuses it into a common operational picture. Then, using the latest advances in machine learning and data analysis, it scans the data for patterns that are not visible to human eyes, helping decision makers understand adversary potential courses of action before they are executed." ***https://www.cbc.ca/news/politics/norad-shield-defence-ballistic-missile-bmd-1.5887192***

Of course, implementation is the key, and Sanders and Wood give useful guidance to firms contemplating a similar shift. These include a list of traits such as "flexible organizational structures" and "integrated work teams," which they see as essential to a successful business model. As they warn, "Companies that mistakenly treat AI as another piece of technology to tack on to their company will go the way of Blockbuster Video." The aim is "not to train humans to think like computers, but how to think *with computers*."

Forecasting how this will play out is hard, but one thing that seems likely is that the boundary between humans and machines will continue to evolve in fascinating ways, and the authors offer helpful glimpses into its future and a road map to help navigate it.

How Will Computers Evolve

One question is how computers themselves will evolve, particularly if and when quantum computers see widespread application. Many of the companies that currently lead in big data, such as Google and Amazon, along with governments and state-led consortia, are investing billions in the development of quantum computers.

As political scientists James Der Derian and Alexander Wendt (2020) note, there is

> *a growing recognition—in some quarters an apprehension—as quantum artificial intelligence labs are set up by tech giants as well as by aspiring and existing superpowers that quantum consciousness will soon cease to be a merely human question. When consciousness becomes a chimera of the human and the artificial, not only new scientific but new philosophical and spiritual cosmologies of a quantum bent might well be needed if we are to be 'at home in the universe'.*

In other words, computers may really start to think for themselves.

Bostrom is perhaps best known for his simulation hypothesis, which states that since computers in the future could one day produce consciousness, "we would be rational to think that we are likely among the simulated minds rather than among the original biological ones" (Bostrom, 2020). The hypothesis is taken seriously by people including Elon Musk, who probably uses it to justify the Tesla share price.

Personally, I hold out hope that we are not just apps on some future teenager's phone. However, it seems likely that the boundary between humans and machines will continue to evolve in fascinating ways, and the piece by Sanders and Wood offers helpful glimpses into its future.

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REFERENCES

Bostrom, N. (2003). Are You Living in a Computer Simulation? P*hilosophical Quarterly*, 53(211): 243-255.

Der Derian, J. & Wendt, A. (2020). Quantizing International Relations: The Case for Quantum Approaches to International Theory and Security Practice, *Security Dialogue*, 51(5):399-413.

Funabiki, S. (2021). Two Brains Are Better than One, *World Finance* (Winter).

Mistry, H.B. & Orrell, D. (2020). Small Models for Big Data, *Clinical Pharmacology and Therapeutics*, Apr. 107(4):710-711. doi: 10.1002/cpt.1770. Epub 2020 Jan. 29. PMID: 31994177.

Commentary:
A Brief Historical Perspective on Integrating New Technology

KEN FORDYCE

There have been substantial improvements in artificial intelligence (AI) technology over the last 10 years. But the challenge remains how to best incorporate this evolving new technology into an organization. The goals are improved decision making and organizational performance—or, as the authors of the article term it, the creation of a *humachine* (Sanders and Wood, 2020).

In this commentary, I will offer a historical perspective on the challenge of creating a humachine. How to best support decision making with technology has been an ongoing challenge for many decades, producing both successes and failures.

Since 1976, first at IBM and for the last nine years at Arkieva, I've observed the efforts in supply-chain management to apply decision technology to further scientific discovery and improve organizational performance. *Decision technology* is an old term, but it's one I prefer because it recognizes a diverse and growing set of technologies (probability and statistical models, discrete optimization, machine learning, expert systems, and more) that helps humans make smarter decisions.

In the 1970s, OR and statistics—the equivalent of today's data science and machine-learning hype—were grounded on four pillars:

1. Humans have their strengths but also weaknesses, such as bounded rationality (Simon, 1947), and organizations as well have cognitive limitations (Galbraith, 1973). This is similar to Moravec's Paradox.
2. Humans are toolmakers and tool users. We make tools to help with physical activities and to augment our cognitive abilities. Organizations must recognize the same need.
3. The tools should support human and organizational decision making—similar to Kasparov's Law.
4. The ultimate use of any invention is often not clear when first deployed. For example, the original role of telephones was envisioned to replace the telegraph by transplanting Morse code with voice. A century later, nearly every desk housed a telephone, and now the phone travels with us while doubling as a camera and avenue to the internet.

In 1977, the best and the brightest in OR were working on how to effectively integrate information and decision technology. Two early applications were the executive information network (EIN)—which enabled executives to keep track of events and finances in the field engineering business (repair of computer hardware)—and the tax optimization model (TOM) to evaluate different tax strategies to legally minimize tax costs.

A huge impediment to these systems at the time was the lack of any display devices that could handle *full screen* (as Windows does today). *Interactive computing* meant punch cards and printed reports. As the above core technologies became commonplace, the new hot technology was decision support systems (DSS).

Two of the original DSS papers were

- *Interactive Computer Systems for Managers: A Modest Proposal* by Peter Keen (1976)
- *Models and Managers: The Concept of a Decision Calculus* by John Little (1970)

In the 1980s, interactive computing became a mainstay of advanced organizations, just as the AI wave emerged. The core AI technologies then were expert systems, search algorithms, natural-language processing, fuzzy sets, and early aspects of statistical learning. Access to the correct data was, then as now, a challenge. But the primary question was how best to use this technology in organizations to support, rather than replace, the human role.

This AI wave culminated in the late 1980s with two books: *Innovation Application* by Herbert Schorr, and *The Rise of the Expert Company* by Turing Award-winner Ed Feigenbaum. Prof. Feigenbaum established the concept of *community intelligence*, which directly addresses organizational cognitive limitations.

> *It is a new kind of entity—a community intelligence born from the collective wisdom of various disciplines, experiences, and points of view, which dynamically disseminate the new intelligence around the same community that engendered it, solving problems that are too tough for us humans to figure out.*

The late 1980s and early 1990s saw the sunset of this AI wave, although the technical innovations continued. We saw the reemergence of *discrete optimization* (mixed-integer linear programming, or MILP) driven by improvements in solvers, hardware, modeling environments, and interest from major industries. Again, the question of how best to use this technology in organizations to support versus replace was primary.

For AI (expert systems and heuristic search) methods in the 1980s and discrete optimization in the early 1990s, there were four primary challenges:

- how to integrate inherently prescriptive technologies into a valuable support role;
- how much detail to put in the models so that the recommendations were realistic but did not overburden maintainability and solve time;
- how to develop the appropriate user interfaces; and
- how to develop data feeds.

The mid-1990s saw the emergence of modern supply-chain management. SCM comprised two primary areas: demand management (DM) and integrated master or central planning engines (CPE). A third area, sense and respond (SR), arrived in the early 2000s.

In DM, the critical challenge was and remains:

- how to develop better statistical methods (now including machine learning) to extract the most information from the data available;
- how to effectively merge statistical methods with human knowledge; and
- how to best manage human expertise.

Support for these challenges is coming from proactive methods involving machine learning (ML). One post about the use of ML in the forecast-value-added (FVA) process begins:

> "If you think machine learning will replace demand planners, then don't read this post. If you think machine learning will automate and unleash the power of insights, allowing demand planners to drive more value and growth, then this article is a must read."
> ***https://blogs.sas.com/content/sascom/2018/04/17/how-machine-learning-is-disrupting-demand-planning/***

The emergence of CPEs is attributable to a combination of technology and business awareness. The technology is the improvement in optimization and heuristic search methods while the business awareness is the recognition that supply chains are ever more complex and require tools to support planner and enterprises, but not replace them. The role of the planner can shift to applying, rather than just generating, results.

IS THERE HOPE, OR ARE WE DOOMED?

So far, I have attempted to provide a limited historical context to the humachine and the challenge of using technology to effectively support decision making. I conclude this commentary with some observations about how effectively we've met the challenge.

- There is evidence that as a new technology emerged it was successfully applied to support decision making and improve organization performance. One source is the Edelman Competition, which has been run annually for 50 years by INFORMS. Its purpose "is to bring forward, recognize, and reward outstanding examples of operations research, management science, and advanced analytics in practice in the world." According to INFORMS, "Edelman finalist teams have improved organizational efficiency, increased profits, brought better products to consumers, helped foster peace negotiations, and saved lives." ***https://www.informs.org/Recognizing-Excellence/INFORMS-Prizes/Franz-Edelman-Award.***

  Papers from the Edelman finalists are published in the INFORMS *Journal of Applied Analytics*. The *IJAA* has focused on the successful integration of technology into organizations, and the articles present the path/process to success as well as the technical details.

The challenges to successful integration of technology into organizational processes are best addressed by small, advanced analytics teams.

- Organizations are generally mum about successes and failures. Often the pattern of successful adoption of technology is resistance, sequence of successes, then stabilization. Sometimes there is "slide back"—referred to as a return to the dark ages. Two specific examples:
  a. Factories that produce wafers and chips (FABs) are a critical underpinning of most products, and shortages directly affect many products. In the late 1970s and early 1980s, FABs did not have relevant time access to production flow data, and so relied on reports printed overnight. When agents of change suggested the use of relevant time data and of AI methods to improve FAB performance, there was great resistance. By the 1990s, however, FABs were commonplace.
  b. In the mid-1990s, the task of creating an end-to-end central plan for a supply chain in one day was considered nearly impossible; getting this done in even 15 days was considered a Herculean task. Today, even small firms create a central plan in under six hours.
- The challenges to successful integration of technology into organizational processes are best addressed by small, advanced analytics teams. The teams should have a skill set that includes programming algorithms, ability to extract insights from flawed data, and the knowledge base to choose the right combination of methods or to create new ways to understand how to nudge an organization from its current comfort zone to its next (more advanced) comfort zone—that is, to function as agents of change.

Embedding a new decision technology must necessarily upset the current social order to become integrated into a new social order: a new application must move from a dream to something an organization cannot imagine life without.

- Agents of change can and do quickly disappear if organizational leadership loses focus on the need for innovation in its core decision technology. This happens easily, despite the mantra of "competing on analytics," especially since the impact is often delayed while the organization survives on past efforts based on manual workarounds. Embedding a new decision technology must necessarily upset the current social order to become integrated into a new social order: a new application must move from a dream to something an organization cannot imagine life without. This must be done while avoiding confusion for the planners and management. A successful agent of change must learn to spot a confused look on a client's face—though it might show for only a moment—and be able to explain the basic logic of the new technology. Over time, the stakeholders will come to appreciate the technology's ability to tackle complexity and will develop confidence in it.

THE HUMACHINE

In conclusion, the question how best to support decision making with technology has been an ongoing challenge. In this context, *The Humachine* by Nada Sanders and John Wood is a must-read.

- It provides an insightful overview of the current challenge presented by promising new technology.
- It explains how to properly integrate new technology with human resources to leverage the virtues of each and avoid the limitations of both.
- It succinctly describes Moravec's Paradox and Kasparov's Law and the path to the humachine.

My one critique is the failure to identify the "smart technology" opportunities that come from analytics other than AI. For example, while the authors note "Even UPS truck drivers are authorized to override the route optimization algorithm," in fact the developers of this application used methods from Operations Research.

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REFERENCES

Galbraith, J.R. (1973). *Designing Complex Organizations*, Addison-Wesley.

Keen, P. (1976). "Interactive" Computer Systems For Managers: A Modest Proposal, *Sloan Manage Review*, 18:1, 1-17.

Little, J. (1970). *Models and Managers: The Concept of a Decision Calculus Management Science*, 16:8, B466–B485.

Sanders, N. & Wood, J. (2020). *The Humachine: Humankind, Machines, and the Future of Enterprise*, Routledge Press.

Simon, H. (1997). *Administrative Behavior: a Study of Decision-Making Processes in Administrative Organization*, 4th Edition, The Free Press.