The take-up of Artificial Intelligence (AI)-enabled systems in organisations is expanding rapidly. Integrating AI-enabled automation with people into workplace processes and societal systems is a complex and evolving challenge. In this context, we look at management issues related to AI-enabled automation and augmentation, and provide insights relevant to integrating people with smart machines to do cognitive work and other types of work as well.

In this article, we provide an overview of how AI is being deployed inside companies, based on findings from very recently available research on AI applications and managerial impacts. We also highlight adaptation in employee roles as companies increase the usage of AI-enabled systems. This includes state-of-the-art thinking on how humans and machines need to work symbiotically to augment and enhance each other’s capabilities. This leads into a discussion on how we fundamentally rethink the standard partnership of human minds and increasingly intelligent machines. We conclude with a statement of the imperative for a new human-machine symbiosis that will help organisations harness the forces associated with the acceleration of change in ways that can lead to growth as well as to productivity increases.

How AI is being deployed inside companies

Three types of cognitive automation applications

Professor Tom Davenport has spent his professional career doing field studies of new ways in which larger corporations have been making use of information technology and reorganising knowledge work. His book, “Competing on Analytics: The New Science of Winning”, originally published in 2007, and revised and republished in 2017, has become a management classic. Over the past four years, he has focused on studying deployments of AI-enabled cognitive systems in the front and back offices of corporations. In a recent joint research with Deloitte, he examined 152 AI deployment projects across multiple industries that are making
use of AI-based systems across a wide range of business functions and processes. Based on this work, Davenport categorises AI system applications into three categories:

- **Cognitive Process Automation**: Automation of back office administrative and financial activities using ‘robotic Process Automation’.
- **Cognitive Insights**: Detecting patterns in data and interpreting their meaning using statistically-based machine learning algorithms.
- **Cognitive Engagement**: Engaging employees and/or customers using natural language processing chatbots, intelligent agents and machine learning.

Of the 152 projects, over 84 percent were focused on process automation or analytics while only 16 percent were focused on engagement. Within this smaller set of engagement applications, the majority were for internal employee engagement, not external customer engagement. Davenport notes that as of 2017, most companies were not yet comfortable enough with cognitive systems to ‘unleash’ cognitive engagement interfaces directly on their customers. My own discussions with companies in Asia that are deploying AI applications are consistent with the findings of Davenport’s U.S.-based observations. In the Asian companies I have spoken with, most of the AI applications are for process automation or analytics. For the smaller set of applications focused on engaging with people, I observed the same trend that companies in Asia often start by using AI-based engagement interfaces for supporting their internal employees to test out its capabilities. Davenport cautioned against embarking on highly ambitious moonshot types of AI projects early in a company’s experience cycle with AI applications. He stated, “our study of 152 projects in almost as many companies also reveals that highly ambitious moon shots are less likely to be successful than ‘low-hanging fruit’ as many companies also reveals that highly ambitious moonshot types of projects that enhance business processes.”

### INDUSTRY FEEDBACK ON AI USAGE

The 2017 Deloitte State of Cognitive Survey, published in August 2017, was based on interviews with 250 executives and senior managers who are “cognitively aware leaders” within “cognitively active companies” that include “some of the most aggressive adopters of cognitive technologies” in the U.S. Other credible surveys have assessed the degree of AI implementation across industries in Asia to be substantially behind the degree of implementation in North America or Europe. As such, this Deloitte survey report will be very helpful to senior managers and executives in Asian companies considering or already piloting AI applications, or still in the early stage of scaling up deployments across their business. Three of the findings from this survey that I would like to highlight are as follows:

1. The companies in the survey with the most experience and most expertise in AI applications (akin to those in the ‘Fast Lane’ in a swimming pool) were much more likely to state the primary benefits of using AI as enhancing the ability to create new products and services or to pursue new markets. In contrast, those companies with the least experience and lowest level of sophistication in AI applications (akin to those who are ‘Waders’ in a swimming pool) were much more likely to state the primary benefit of using AI as reducing headcount through automation. The Deloitte survey summarises this situation by saying, “...while the Fast Lane wants to innovate, the companies in the Wader segment want to automate.” Why is this so? The Deloitte survey report postulates, “... it is telling that so many Fast Lane respondents, who have gained stronger returns from cognitive tech deployments than Waders, see new Wagner opportunities as their main benefit. Perhaps this is because their senior leaders understand the potential of cognitive technologies to improve their products and services.” In other words, those companies that lack sufficient experience with using AI to enhance products, services and top line revenue growth opportunities will revert to the more conventional assumption that the primary benefits that can be realised is bottom line cost reduction through headcount elimination.

2. Almost half of those interviewed said their top challenge with AI applications related to the difficulties of integrating these new efforts with their existing processes and systems. Companies deploying AI systems based on statistical machine learning methods or on expert/rule-based methods more often referred in integration challenges as their top challenge. This is an important reminder that most AI applications need to be integrated into the existing organisation in order to realise business benefits. It highlights that the majority of your IT department—those personnel who are not AI experts—still have a very important role to play in your organisation. You need them to make it possible for the new AI systems to have access to your various data sources. You also need them to integrate the outputs of the AI systems with your existing legacy systems.

3. Most companies interviewed said they have not experienced substantial job losses to date as a result of deploying AI technologies, and they do not predict substantial job losses in the future either. The survey report notes, “In interviews, most companies say that augmentation has so far been much more common than job elimination through automation.”

### SINGAPORE EXAMPLES

Two examples of companies in Singapore that are effectively deploying AI and machine learning systems are shown in Figures 1 and 2 below. The first example is Vodien Internet Solutions, a small and medium sized enterprise (SME) with annual revenues around US$10 million per year that provides web hosting services and solutions for organisations in Singapore and the ASEAN region. Vodien’s total employment is just under 150 people spread across four ASEAN countries. Over 35,000 companies in ASEAN, mostly SMEs, use Vodien’s various web hosting services, resulting in a total revenue base of over 210,000 individual users to support. As a SME, Vodien is an important illustrative example because SMEs account for a significant fraction of both national employment and gross domestic product across all ASEAN countries and across the other Asian countries as well. For the reasons, it is important for ASEAN and other Asian countries to pay close attention to the extent of growth their SME base is making in adopting AI in ways that lead to business improvement.

As a SME, Vodien does not have much money to burn. While they are an IT hosting services firm with very capable IT technical staff, they cannot afford to have a dedicated corporate AI team, and to-date, they do not have AI specialists on their staff. Their technical staff and executives did their own self-study to get familiar with AI technology and how AI capabilities could be used within the specific setting of their business. Vodien started its AI journey by concentrating on a few critical internal process automation needs together with the internal analytics needs (Figure 1). They were able to do trials and then proceed to production deployments relatively quickly. In addition, Vodien also partners with their external software solution vendors who had already developed AI capabilities. The combination of both internal and external AI capabilities were incorporated into the specific types of software application products that were being used within Vodien. Based on this successful experience with using AI within a few targeted application areas, they are now in the process of exploring how to use AI capabilities to engage and support their internal employees as well as their customers. This pattern of initially focusing on internal process automation and analytics, and then progressing onward to exploring how AI can be used for employee and customer engagement, reflects the same pattern reported by Tom Davenport in his U.S. studies of larger companies.

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**VODIEN INTERNET SOLUTIONS**

<table>
<thead>
<tr>
<th>Users of the System</th>
<th>Type of AI and ML</th>
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<td><strong>Process Automation</strong></td>
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<td>External</td>
<td>Chatbots for Call Centre Support (under consideration)</td>
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<td>Internal</td>
<td>Date Centre Optimisation Support</td>
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<td>Security &amp; Data Pattern Analysis</td>
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<td>Intelligнт Support for Call Centre Staff (under consideration)</td>
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**FIGURE 1** Source: Author’s own

The second example is the Changi Airport Group (CAG), the corporate entity that manages and develops Singapore’s highly acclaimed airport. CAG is a large organisation in terms of total employment, total revenue, and breadth and depth of corporate capability. The total Changi Airport ecosystem, including the many vendors and service providers employed on the airport premises, is many times larger than CAG itself, and the CAG team has to orchestrate and oversee the smooth and reliable functioning of this total ecosystem. CAG is a combination of
running a company and running a microcosm of an entire city (as the airport is, in essence, a small city in its special way). Figure 2 describes a subset of the AI projects that CAG has been working on. Like many other organisations, getting started with AI applications, CAG started its journey by concentrating on specific task automation, such as limited chatbot implementation and using AI in image recognition application.

About a year ago, CAG launched a strategic initiative targeted on substantially improving their current ability to predict flight arrival times for long-haul inbound international flights (i.e., inbound flights with trip flight durations longer than five hours). The scheduled arrival time is obviously known in advance, but flight arrivals very often deviate from the scheduled arrival time. Even if the flight departs on time from the originating airport, it could arrive late (or early) for a variety of reasons. And even it is known that a flight will have a delayed departure from its originating airport, it may or may not be able to make up some amount of the lost time. In short, it is much more difficult than most airport users appreciate to know exactly when a long haul inbound international flight will actually arrive at the gate of its destination. And why is the ability to predict gate arrival times so important to CAG? Because so many processes and operations within the airport are triggered by the plane’s actual (versus planned) arrival. To appreciate how many different types of resources within the airport ecosystem need to know and respond to the exact arrival time at the gate, just envision all the things that must happen once the plane touches down on the runway and taxis to the gate; the aircraft parks at the gate; passengers disembark and arrive at the immigration queues; all aspects of baggage handling; retrieving their bags at the baggage claim; and even at the taxi queue. Then of course, there are all the processes related to the preparation for the next aircraft that is due to arrive at the same gate.

As straightforward and basic as it may seem (to non-experts in airport operations) to know exactly what time the inbound flight will arrive at the gate, it has not been possible until now to make this type of prediction with the required accuracy, with enough advance lead (at least two hours in advance, otherwise it may be impossible to change plans) and at the scale of operations required (given the large number of flights that are scheduled to arrive every day) to enable substantial improvements in resource planning and optimisation of airport resources. Over the past 12 months, however, CAG has been able to achieve this prediction capability for its long-haul inbound flights. This has been a great achievement for Changi Airport, and a great demonstration of how AI can be used in ways that will lead to substantial improvements in service delivery quality and productivity. CAG is now in the process of working on a number of extensions and enhancements that build on this foundational capability, from better synchronised resource management for all the people and equipment who are triggered by a gate arrival, to finding ways to get the prediction even a few hours earlier to further improve resource planning, and to applying this same type of approach to the large volume of short-haul flights (within a two- or three-hour flight time) that arrive at Changi.

This was a large AI system effort that had multiple parts. There was the enormous data integration effort that involved bringing together existing types of historical data and real-time data that were already available for IT systems usage. It also involved bringing in new types of historical data and real-time data that were either not being used for this type of purpose, or was not previously available. There was the effort to use AI methods to enhance existing algorithms and models that were already in use for this purpose. There was another stream of work to create new models based on new methods and to combine this with and/or compare this against the existing and enhanced versions of the previously used approach for this type of prediction.

As was a large project involving so many different types of expertise, and CAG wanted to move quickly, they worked with external technology partners who were familiar with AI methods for this type of prediction and with airport domain settings. CAG’s flight time arrival prediction system is a good example of using AI to create new or vastly improved capabilities without putting existing employees out of a job. By improving Changi Airport service delivery while at the same time improving resource efficiency, this new AI application helps to improve the airport’s competitive position, and by doing so, makes it more likely that overall airport demand will continue to increase even with competition from other airports. It would mean that employment for airport service support staff would continue to increase. This is a good example of how humans and intelligent machines can, and need to, work together to bring about major process improvements and more productive allocation of resources. The AI system provides the predictions of arrival times considering many factors. Airport operations planners and supervisors are needed to make the decisions on what to do once they know with a high degree of certainty the time the flight will actually arrive, based on the prediction of the AI system. Based on everything else they are aware of at the airport, the human planners and supervisors work with the systems to devise an adaptive plan for how to deal with the situation depending on how early or late the flight will be. The complete process from runway landing to gate to immigration to baggage and to taxi gets smoother, easier and more efficient. Deployments for service staff and resources can be planned and optimally allocated. Resource flows are better managed. Costs are reduced and customers are happier.

Changi is also in the process of testing and deploying AI-enabled applications for engaging with its internal employees, and for engaging with customers. The third column in Figure 2 shows that CAG is in the process of introducing chatbots for engaging customers and other internal applications for employee self-service support.
providing five alternatives for employees to renegotiate their relationship with smart machines being used to partially or fully automate cognitive work, and for how employees can realign their workplace contributions. Figure 3 below illustrates these five ways of stepping by Davenport and Kirby in an original way, as their explanations of this framework in their earlier Harvard Business Review article and their follow on book did not contain this type of illustration.

One of these five ways that people can ‘step’ in response to the inevitable increase in the use of AI-enabled smart machines, the one that involves the largest number of people is the ‘step in’ role. This is where a person who has deep experience with a process or functional area learns to work symbiotically with the smart software application. For example, the person will know the best sources of data to use to train the machine, or they will know when there are special circumstances that apply that invalidate the system’s outputs because these special circumstances are not reflected in the training data, or when factors in the environment have changed sufficiently to warrant an update of the training process and model.

The other four types of stepping are also important, but I believe three out of these other four stepping roles will involve fewer numbers of people than those who need to learn how to step in. ‘Step forward’ refers to those in the organisation who will be the technology designers and engineers, and the software system creators, consultants and implementers. This includes the analytics specialists and the data science professionals who develop, test and deploy the new models that integrate methodologies from statistics, other areas of advanced analytics, and various fields of AI including machine learning. Across user organisations and technology and service providing vendor organisations, there will indeed be a steadily growing demand for those who can step forward in this way. While new jobs are rapidly being created for this type of role, and this will continue, I still believe it will involve far fewer people than those who will need to step in or to substantially change the nature of their work in other ways.

‘Step narrowly’ refers to those who will keep on doing some type of highly specialised work they currently do, and continue doing it in the same way as they have been doing it. While in principle that type of work could be done by AI systems, Davenport and Kirby note there will always be some type of highly specialised work they currently do, and some very capable human has to motivate and persuade the client to accept and follow the plan. Another part of this step aside role is to continually follow up with the client to reinforce the need to follow the plan, as well as to see if the client’s situation has changed in ways that would require the creation of a new plan. A similar situation is likely to occur in parts of medical consultation, diagnosis and treatment recommendation. There could be a need for a large number of people to step aside in this way, and to focus on the very last step, and perhaps the most crucial step in the value chain, which is engaging with the customer in ways that close the loop and realise value, both for the customer as well as for the service provider.

A less desirable and non-income producing way to end up stepping aside is to be automated out of a job. We will come back to this issue of AI for automation versus for augmentation in a moment.

The Five Ways of Stepping is a simple yet clever and powerful conceptual framework. It helps managers and executives think through the adaptations that employees at all levels and across all functions will need to make as the deployment of AI applications continues onward, and continues to accelerate. Additional opportunities for stepping that these two business thinkers implied but did not explicitly discuss are the key interface roles between the five stepping roles. For example, I believe there will need to be substantial numbers of people working the interfaces between the ‘step in’ role, and the four other roles. Maybe the same people doing the ‘step in’ role will handle this. But it is easy to think of many situations where there will be a need for additional people to be that special humbly intelligent and adaptive ‘agent’ who serves as the interface between those focused on stepping in, and those focused on stepping forward, stepping aside, stepping up, and even stepping narrowly.

**AUTOMATION V. AUGMENTATION**

As part of the conceptual framework for Five Ways of Stepping, Davenport and Kirby called for an approach to integrate humans and smart machines that emphasised...
augmentation over automation. As they stated in their June 2015 Harvard Business Review article “Beyond Automation”,

What if we were to reframe the situation? What if, rather than asking the traditional question: What if tasks currently performed by humans will soon be done more cheaply and rapidly by machines? We ask a new one: What new feats might people achieve if they had better thinking machines to assist them? Instead of seeing work as a zero-sum game with machines taking an even greater share, we might see growing possibilities for employment. We could reframe the threat of automation as an opportunity for augmentation.9

I created two images (Figures 4 and 5) to visually summarise the key points that Davenport and Kirby emphasised regarding an automation mindset versus an augmentation mindset that are important for executives to keep in their mind when they oversee strategic initiatives and investments in AI within their own organisation to improve their processes, services and products.

Davenport and Kirby hit the nail right on the head when they came up with these two summary statements:

• Employees hate automation and love augmentation.
• The same tools can be used to automate or augment, but the intents behind the use of these technologies are 180 degrees apart.

Executives and managers who do not take these two statements to heart will encounter huge obstacles and fierce resistance when they try push AI deployment initiatives forward in their organisations. As noted earlier in this article, from the work of the Economist Intelligence Unit 2017 Global Survey on AI usage in industry, the overall broad base of companies in ASEAN and Asia are still lagging behind their counterparts in North America and Europe with respect to the degree of AI implementation—despite the great success of a relatively small number of well-known AI implementation superpowers in Asia, and particularly in China. As the majority of ASEAN and Asian companies are just setting out on this journey, it is important for them to pay attention to the comments of Davenport and Kirby highlighted above if they want the cooperation and support from the people within their own companies.

Pursuing AI system developments with a mindset of augmentation versus automation makes all the difference to employee morale.

HUMAN AND MACHINE HYBRID ACTIVITY

The concepts of augmented intelligence and human-machine symbiosis can be traced back to the activities of U.S. computing pioneers J. C. R. Licklider and Douglas Engelbart in the 1950s, and to their respective writings on these topics that were published in the early 1960s and onward. In 1960, Licklider published an article titled “Man-Computer Symbiosis” where he stated the goal of enabling people and computers to cooperate in making decisions and controlling complex situations
Engelbart is acknowledged as the creator of the concept of "Augmented Intelligence." In 1962 he published a report, "Augmenting Human Intellect: A Conceptual Framework," which outlined a framework for the use of advanced technology to augment human intellect. The report aimed to provide guidance on how to use computers to enhance human capabilities for complex tasks.

Since the publication of Engelbart's report, researchers and companies have been working to develop AI systems that can be used to augment human intelligence. The concept of "Augmented Intelligence" has been developed over the years, with notable milestones such as the "Symbiotic Augmentation" concept proposed by Liklider in 1960.

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abilities of any human. For example, AI-enabled analytics systems can process vast amounts of data at superfast speed, and use computational methods and models to quickly identify patterns, make predictions, or make choices based on consistently logical analysis of all this information. In this way, the AI system amplifies the cognitive capabilities of a human. Using extended reality (augmented reality and virtual reality), a human can engage with vast amounts of information or with high-dimensional information in ways that would not be possible otherwise. Or a person can use gestures or voice to engage with machines, or with people in other locations. This is how AI systems augment people through enhanced ability for interaction. Mobile robots can bring things to people, or can carry heavy loads for people, or help with physical parts of tasks that are damaging to people. These are examples of how AI-enabled machines augment humans through physical embodiment.

Daugherty and Wilson call for humans and AI-enabled systems and machines to fill the missing middle by working closely together in new types of roles with new kinds of collaborative partnerships. They provide a strong incentive for moving in this direction, and additional support for why managers should use AI as a means for augmentation rather than as a means for automation. They conclude, “In our research, we found that companies that use AI to augment their human talent while reimagining their business processes achieve step gains in performance, propelling themselves to the forefront of their industries. Firms that continue deploying AI merely to automate in a traditional fashion may see some immediate gains, but will not experience the step improvements to performance that those firms with AI as a means for augmentation rather than as a means for automation will see.”

McAfee and Brynjolfsson state their views on the limitations of human and machine hybrid activities.

**Human and machine hybrid activities**

- **Cars**, **buses**, **trains**
- **Arms**, **limbs**, **heads**
- **Humans complement machines**
- **AI gives humans “superpowers”**

**THE MISSING MIDDLE**

**Figure 6** Source: Author’s adaptation from the work of Daugherty and Wilson (2018)

**Rethinking the standard partnership**

In 2017, MIT Sloan School researchers, Andrew McAfee and Erik Brynjolfsson, published the book, “Machine, Platform, Crowd: Harnessing our Digital Future,” which was their third book on factors driving the digital economy. 15 It is divided into three parts—Mind and Machine, Product and Platform, and Core and Crowd. Each part describes the great rebalancing that is presently taking place across industries throughout the global economy and more broadly across society. Their premise is that these three concurrent and interconnected rebalancings are the main forces driving current, emerging and foreseeably future trends in the digital economy.

The section on Mind and Machine focuses on the changing relationship between human minds and increasingly intelligent machines in the workplace. McAfee and Brynjolfsson articulate what they call the “standard partnership between minds and machines” that has developed within organisations (in both the private sector and the public sector) that have been using computers to automate work tasks since the 1970s. 16 Their key point is that within the next decade there will emerge a vast difference between the winners and losers, a difference determined not on whether an organisation has or has not deployed AI, but rather on whether the organisation is using AI as a means for augmentation rather than as a means for automation. They conclude, “In our research, we found that companies that use AI to augment their human talent while reimagining their business processes achieve step gains in performance, propelling themselves to the forefront of their industries. Firms that continue deploying AI merely to automate in a traditional fashion may see some immediate gains, but will not experience the step improvements to performance that those firms with AI as a means for augmentation rather than as a means for automation will see.”

McAfee and Brynjolfsson state their views on the limitations of human and machine hybrid activities.

**TWO MODES OF HUMAN THINKING**

McAfee and Brynjolfsson refer to System 1 and System 2 modes of human thinking, and use these concepts to explain important limitations of human judgement and decision-making vis-à-vis data driven, algorithmic and model-based judgement and decision making. The psychologists Keith Stanovich and Richard West in the journal, “Behaviour and Brain Science” first introduced the specific terminology of System 1 and System 2 modes of human thinking in 2000. 17 The Stanovich and West article that first used this terminology was a part of a vast body of scientific research tracing back to the 1970s (and even earlier) that has focused on understanding the differences between so-called normative (logically rational and optimal) decision making and descriptive (actually observed) human decision making, and on explaining the reasons for why humans so often deviate from normative (and hence logically optimal) choices in their judgements and decisions.

The terminology of System 1 and System 2 modes of human thinking and the associated cognitive concepts were more widely introduced to the general public and mass media with the publication in 2011 of the book “Thinking, Fast and Slow” by Daniel Kahneman. 18 Kahneman had received the Nobel Prize in Economics in 2002 for his work with Amos Tversky (who was already deceased at that time and therefore not eligible to be a co-recipient of the Nobel Prize). The Nobel Prize committee noted that Kahneman received the Economics Prize, “...for having integrated insights from psychological research into economic science, especially concerning human judgment and decision-making under uncertainty.” 19

**Human Minds**

- **HiPPO**
- **Highest Paid Person’s Opinion**
- **Especially strong influence on judgment and decisions**

**HIPP0**

- **Subject to the same limitations as any other human mind**
- **Yet no protection from especially strong influence**
- **Often destroys value when irrational inputs dominate judgment and decision process**

**Machines**

- **The basic math, all calculators, math-based models**
- **Data related transaction execution, transaction monitoring and reporting**
- **Network connectivity, transmission of data and info, sharing of digital data and info**

**People**

- **Make decisions, exercise judgment**
- **Use intuition, be creative**
- **Interact with other people to solve problems, to take care of customers, employees**

**1. The Standard Partnership of Minds and Machines (from ~1980’s to current)**

- **Use both System 1 and System 2 modes of thinking**
- **Are systematically biased when using System 1 heuristics**
- **Depart from rational logical thinking due to bounds on cognition, emotion and motivation, and other factors**
- **Cannot fully control when their System 1 mode of thinking is activated**
- **Not fully aware when cognitive limitations are affecting rational judgments and decisions**

**2. Accepting our Cognitive Limitations**

**HIPPO**

- **Subject to the same limitations as any other human mind**
- **Yet no protection from especially strong influence**
- **Often destroys value when irrational inputs dominate judgment and decision process**

**Figure 7** Source: Author’s adaptation from the work of McAfee and Brynjolfsson (2017)
I provide additional information on the descriptions of System 1 and System 2 modes of human thinking in Figures 8 and 9 below. The figures illustrate well-documented biases in human judgement and decision-making that result from the fact that in many situations, especially when there is uncertainty or when people are under time pressure or emotionally aroused, they unavoidably resort to System 1 heuristics. In their book, McAfee and Brynjolfsson provide summaries of recent studies that demonstrate the weaknesses of System 1 thinking and intuition, even with experts.

Based on the huge body of evidence on the nature of human judgement and decision-making, and on how expert decision-making compares to the results of statistical models (when the data is available and the models can be validated), McAfee and Brynjolfsson come to the following sobering conclusion, "...that we need to rely less on expert judgement and predictions." Their justification is as follows: "In case after case, when a model can be created and tested, it tends to perform as well as, or better than, human experts making similar decisions. Too often, we continue to rely on human judgement when machines can do better."

McAfee and Brynjolfsson go on to raise the question about what role should people play in making decisions. It is a complicated question. Even though the results are overwhelmingly clear that statistically-based models usually outperform human expert judgement in those situations when the models and supporting data are available and when the models are properly validated, most organisations exist in dynamic, uncertain and ever-changing environments. There will always be many situations where the necessary data is not available, or where a model has not yet been created, or has not been sufficiently tested and reliably validated for a new or changed situation. On the one hand, we know from decades of scientific research on human judgement and decision making that the System 1 mode of thinking often leads people to depart from normative logic, and often leads to questionable or outright wrong choices and decisions. On the other hand, these same cognitive mechanisms give people a range of truly remarkable capabilities. These include:

1. Abilities to understand physical, social and situational context;
2. Abilities to understand the intent of other people as well as the needs of other people;
3. General purpose, common-sense reasoning ability that does not require domain-specific training examples;
4. Escalation of commitment
5. Overconfidence bias
6. Common biases resulting from the “Big 3” heuristics
   a. Availability heuristic
   b. Representativeness heuristic
   c. Confirmation heuristic
7. Limitations due to bounds on cognition
   a. Bounded rationality
   b. Bounded awareness
   c. Bounded willpower
   d. Bounded self-interest
   e. Bounded ethicality
8. Influences of emotional and motivational affect
   a. Biases resulting from emotions and from self-serving motivations versus from cognitive limitations
9. Framing of information affects decisions
   a. Biases related to a sequence of decisions occurring after decision makers commit themselves to a particular course of action
AI can be used for augmenting human intelligence and capabilities across all business settings. All three studies are telling us to get ready for big changes that are related to the increasing use of AI-enabled systems and machines within every type of workplace. All three studies provide evidence that these changes are already underway, and make it clear we are just at the beginning of what will be a long and profound transformation period.

Perhaps there are advantages for the vast majority of ASEAN and Asian companies that have not yet started down this transformation pathway. They can start now, and take advantage of the lessons learned to date from the experiences of the many firms in North America and Europe, as well as from the Chinese AI superpower companies, that have already started on this transition. They can benefit from the findings of the studies summarised in this article. Also, the firms in this region who are just starting now can benefit from the fact that the AI software and solution vendor community has more experience, and more robust product and service offerings.

In the discussions above on how the partnerships and nature of symbiosis between human minds and computer-based machines need to change, the emphasis has been on office, administrative and commercial types of work. The same point has to be extended to the many other types of work settings where decision-making occurs in the context of physical interactions and physical service delivery. This includes many different types of service work, field-work, transportation work, infrastructure related construction and maintenance work, manufacturing work, and logistics work. Similarly, the discussion above on how to put human intelligence in the loop in intelligent ways, in partnership with increasingly intelligent machines, emphasised office, administrative and commercial work. This same point has to be extended to other types of work settings where decision-making occurs in the context of physical interaction and physical service delivery.

In essence, this 'Second Machine Age', a term MacAfee and Brynjolfsson coined in their prior book, will propagate across all sectors of the economy and will result in most types of work being transformed in one way or another. The imperative of a new human-machine symbiosis

The earlier waves of machine automation were built around economies of scale. Automation was used to increase efficiency and raise productivity. Previous generations of automation, including computerisation, were very limited in intelligence, and as such, relatively inflexible. As a result, a requirement for automating and computerising in prior machine ages, up to very recently, has been the strict enforcement of standardisation combined with related efforts to constrain allowable change and adaptation. In other words, automation and computerisation gave us efficiency and productivity but at the cost of constraining our ability to change and adapt. Companies like Toyota and Exxon taught the post-World War II world how to use automation and computerisation to take advantage of economies of scale across the full spectrum of the product realisation life cycle, from earlier stage product development, into manufacturing with all of its required supply chains, and through final delivery via global distribution channels. Toyota and Exxon achieved significant positions and dominance in their respective global markets for decades through their ability to master and exploit economies of scale. While they respectively introduced new products periodically in response to market change, they had to carefully constrain and manage the rate and extent of change as it was so expensive and time consuming to re-engineer their highly standardised, automated and inflexible processes.

We have now entered a new machine age of the lessons learned to date from the experiences of the many firms in North America and Europe, as well as from the Chinese AI superpower companies, that have already started on this transition. They can benefit from the findings of the studies summarised in this article. Also, the firms in this region who are just starting now can benefit from the fact that the AI software and solution vendor community has more experience, and more robust product and service offerings.

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are flexible, adaptable and dynamic, though not necessarily
and standardisation and stabilisation by reducing variances
requires change, and adaptation to uncertain and rapidly
of human labour and minds.
feedback systems will be the ones that most effectively master
analytics and AI to automate and augment their closed loop
needs to happen, and to predict what will happen, will move
environment, to make sense of the data, to identify what
data at speed and scale to sense its external and internal
have so clearly demonstrated, the company that can best use
learning.
executing the PDSA type of closed loop feedback system,
making predictions. This new wave of AI-enabled smart machines is to find the right combination
of using highly adaptable and versatile human employees with
highly efficient and consistent machines that are increasingly
intelligent, though in limited ways. Even with the continuation of remarkably rapid advances in AI technologies and applications, humans will be still more, versatile, more adaptable, and more capable of comprehending and interpreting
unquantifiable contexts and more capable of generating ideas and possibilities that do not require prior experience or available data.
Humans are key to our ongoing ability to thrive on
change. Intelligent machines are key to our ability to move
forward at speed, at scale, and at high levels of productivity.
We need to simultaneously respond to increasing rates of change in beneficial ways and also achieve higher levels of
efficiency and productivity. Going forward, we need a new level of human-machine symbiosis so we can leverage this
new generation of intelligent machines to augment the innate
and remarkable capabilities of our bodies in ways that enhance
business and organisational capabilities for both adaptation and productivity.

References

1. Thomas H. Davenport and Jeffery L. Kulesh, “Artificial Intelligence for the Real
World: Don't start with Mosaics,” Harvard Business Review, January-February
2000, pages 108-116. This work is substantially expanded upon and further

2. Deloitte, “Deloitte State of Cognitive Survey,” August 2017. Some of the results of this Deloitte survey are included in the Davenport and Kulesh, 2010 Harvard Business Review article, as Deloitte was one of the final authors of the report summarising this Deloitte survey, and Kulesh was a contributor.

3. The Economics Intelligence Unit, “Artificial Intelligence in the Real World,”
“January 2017. This survey is based on interviews with 205 executives worldwide completed in 2016, of which 53 percent of respondents were from Asia. The EIU survey team constructed an AI Implementation score for Asia, Europe and North America based on their criteria. The implementation score was lowest in Asia, where implementation was in a more nascent stage compared to the other regions. They found there was a higher degree of AI-related exploration, experimentation, application and widespread deployment in North America and in Europe compared to Asia, while there are several well-known AI powerhouses in China (Alibaba, Baidu, Tencent), the EIU survey reflects the broader pattern of AI adoption across all regions of the economy in Asia.

4. For example, in Singapore, SMEs, defined as those with annual revenue of S$400,000 or less, account for 50 percent of national employment, and just over one-third of gross domestic product. According to the official Singapore SME website (www.sme.gov.sg), SMEs in ASEAN member states account for between 24 to 27 percent of national employment, and between 23 to 30 percent of gross domestic product.


6. All illustrations attributed to Secure Mission (adapted from the published content of other authors) were created with the substantial assistance and contributions of Justin Ozuna of Scientific Reach, http://www.scientificreach.com/.


11. When Enufield submitted his report's copy proposal to the U.S. Department of Defense, J. C. G. Liedlhuber had recently assumed a position as Department of Defense's Advanced Research Projects Agency (ARPA), with responsibility for giving out grant money to support developments in the computing area. Liedlhuber decided that this was not the best report that Enufield's proposal. Example of innovative
data gave out of Enufield's IBM program on augmenting intelligence are described at http://diaport.isju.org/library/enufield-1962-12-07-05-00.pdf.

12. A comprehensive summary of parallel developments of AI for replacing and replacing the human versus AI for augmenting the human and the role of Homo sapiens, “The Human-Computer Interdependence,”
progress and gizmos created the digital revolution, Strom & Strassen, 2014, see Ch 13, Aide Forrester.


14. According to Daugherty and Wilson, the first wave of business process
transformation occurred around 1988 with the Ford Motor Company's
production of the Model T using standardised assembly lines. This was the
beginning of the age of standardisation and production. The second wave started
in the 1970s, continuing into the 1980s and 1990s with the widespread
commercialisation of work processes that occurred at the time as a result of
the diversification of computer (mini computers, PC, more distributed
computing) beyond mainframes, and the emergence of various types
of enterprise software systems. They refer to the current and emerging business
process transformation efforts as the third wave, with the key distinction of
this current wave being the ability to create processes that are flexible, adaptable and
able to operate in the same way, at the same rate, without any loss of
efficiency and productivity.