



WORKING WITH SMART MACHINES

Insights on the future of work.

By Tom Davenport and Steve Miller

Judging from recent announcements by companies and research and development (R&D) organisations, Artificial Intelligence (AI) systems seem to be used everywhere across the world of work, in every industry setting and job role.¹ Well, yes and no. *Yes*, because in almost every industry, many companies are already using AI-based systems in one way or another as part of their regular everyday work. Also, there is a wide range of job roles that have been affected by augmentation, automation, or hybrids of both types of usage. *No*, because successful, especially larger scale, usage of AI systems is still highly concentrated within a fraction of companies worldwide that comprise the potential user base. Furthermore, the overall ‘density’ of actual AI usage embedded into everyday work processes is still low. In fact, most companies are not yet familiar with these systems.

In this article, we share our observations on how and why AI-based systems are being deployed. We look at how these systems have been integrated into existing and new work processes, especially the implications for the changing nature of work and how it will be conducted in future with AI-based smart machines. This will help companies that are in the earlier stages of considering, planning, or deploying these systems to know what to expect from recent developments in practice.

We draw our analysis from 24 case studies that we have recently completed on AI system usage in actual operational settings. This involved in-depth conversation with senior project leaders and direct system users in each case (refer to Table 1 for our assessment on the primary purpose of the AI system usage in each case).

In all the cases, the companies achieved substantial productivity improvements as a result of deploying these

systems. There were three cases of full automation: one resulted in the elimination of a job without redeployment, while in the two other cases, employees were redeployed to other parts of the work process that required human capabilities. In the remaining 21 examples, the AI system was used to augment and support its human users. Both work process capacity and quality were substantially enhanced, enabling the organisations to scale output without having to proportionally increase the supporting labour input. In several cases, the AI system enabled a reinforcing cycle of productivity improvement as frontline staff gained breathing space and time to perform new tasks or work on a new business process.

Ecosystems for supporting AI applications

From our cases, we identified two types of supporting ecosystems that are needed to successfully deploy AI systems in business settings: one is technology-based, and the other is people- and job role-based.

TECHNOLOGY-BASED ECOSYSTEM

Many cases involved new digital platforms and intelligent case management systems.

Platforms

Platforms are the supporting systems underneath the AI applications that do the heavy lifting for acquiring, integrating, and managing the various types and stages of data used. They are the less sexy but no less substantive component of the overall system that makes AI work in practice. Without the underlying platform, the AI system and the workers who use it cannot operate effectively.

AI-enabled decisions, such as classifications, predictions, recommendations, forecasts, and optimised execution plans, need something to happen before they can occur and after they are made. In most cases, data needs to come before the decision. After a decision is made, a series of follow-on transactions and sub-decisions must be activated to support it. Platforms enable this end-to-end flow, from providing the inputs to the AI application to handling the outputs, and are used in three ways:



Exploration support platforms

The highest level of human involvement comes in platforms designed for data exploration and support of an ultimately human interpretation and decision. The functions of the platform include i) access to data, queries, and analytics; and ii) using AI models based on machine learning (ML) or natural language processing that allows sensemaking, interpretation, and supporting situation assessment. The mode of usage is open-ended, largely unstructured, and flexible. The downside of this flexibility is that users typically must possess a high level of skill and domain knowledge to engage productively with these platforms.



Transaction support platforms

Some platforms are primarily intended to perform repeated business transactions with varying degrees of complexity. AI is used to improve human decisions as part of the transaction. Any application where the AI-enabled system provides a human with an ordered list—ranked by most to least probable, or most recommended to least recommended—would be an example of a transaction support platform. A common example is using an AI lead scoring application to rank the priority of sales calls where the platform is a customer relationship management (CRM) system from vendors such as Salesforce, Oracle, and SAP. A more complex setting would be using the ML tool for cyberthreat attribution where the system provides the expert analyst with probability-based scores to assess whether various threat clusters are from new or recognised cyberthreat actors.



Automated decision platforms

Some platforms make automated decisions without any human involvement. A human observer may or may not be able to check the decision or determine why a particular decision was made. These platforms typically produce highly structured and data-driven decisions, which need to be made quickly, often faster than a human can keep up with. They typically do not involve expensive outcomes or costly mistakes. An example of such a platform would be the ‘programmatic buying’ systems used to place digital advertisements on publishers’ websites. Such decisions often need to be made in milliseconds.

Platforms are critical to the success of most AI systems in business settings. Strategies and decisions about AI usage in a company need to address explicit issues about the underlying platform, including:

- For each AI application, what type of platform is needed?
- Should the company build a number of single-use platforms or fewer multi-functional ones?
- How feasible is it to acquire or embed AI capabilities into existing transaction platforms?
- What type and degree of human involvement is desirable for the exploratory support platforms and transaction support platforms supporting human decision-making?
- How can human or machine oversight be provided to prevent ‘drift’ or unintended consequences due to changing conditions for the fully automated platform type?
- How will the choice of platform impact workforce skills and change job roles?

Platforms have strong implications for the groups and job roles in the company that produce data feeding into the platforms, and for those involved in the various stages of the AI/ML pipeline for development, deployment, and ongoing support. They require large amounts of data, integration with existing systems, and high standards for performance and site reliability. Even when using vendor products and external system integrators, it will be necessary for internal information technology (IT) or data engineering groups to handle substantial aspects of the work required to develop or deploy these platforms. Therefore, people in both IT and business roles involved in creating and

maintaining these platforms need to collaborate with the internal or external data scientists who design and implement the AI algorithms at the foundation of these platforms.

Intelligent Case Management Systems

Computer-based case management systems (CMS) bring all the required data and forms to a worker to complete an entire case or unit of work online. They not only eliminate manual paper flows, but also integrate inputs from disparate online data sources and support tools, and automate workflow. While online CMS have been in use for decades, prior generations of such solutions generally did not use AI. More recent CMS incorporate AI and robotic process automation (RPA) capabilities, and have become much more intelligent and capable. We encountered the usage of these systems in many of our case examples of people working closely with AI in their jobs.

CMS have some commonality with some of the platforms we describe: they are involved with the integration of data and the management of workflows, although often in different ways. In most instances, platforms reside underneath the applications used by end-users, whereas CMS are a type of end-user application environment. Given the traits of intelligent CMS and their implications for work, they are worthy of being highlighted in their own right.

We observed three major functions being performed by intelligent CMS:



Workflow management

The system brings the work to the worker, supports and automates task execution, keeps track of task- and case-level completion status, and acts as the primary interface with the work to be done. The system also provides shared visibility of case status to everyone involved in the end-to-end workflow execution and to management.



Prioritisation

AI-enabled CMS can also prioritise the most important cases or transactions within a case to address, for example by ordering them according to predicted profitability, propensity to buy, risk level, or threat impact, depending on the specific domain of the casework.



Recommendations

With earlier generations of CMS, for the most part, the worker had to assimilate the information, assess the situation, and make judgments and decisions as required. It was more a paradigm of information support than a system-driven decision recommendation. The current generation of AI-enabled CMS can use available data and automated decision-making algorithms to make recommendations or even preliminary decisions. An underlying platform supporting the CMS may be needed to collect and integrate the available data required to make an AI-assisted decision.

In the cases that used intelligent CMS, the human user had the ability to review, modify, or override the decision by the smart system. Almost all the users could be described as knowledge workers, where the majority were well-educated and knowledgeable about their job situations, and the specifics of their work tasks. Given that these employees were able to modify the decisions recommended by the case management system, they had to have a practical understanding of how the system made decisions and what data it relied upon to do so. Only with that knowledge can they be comfortable in questioning or overriding the system’s decisions and recommendations. Employers need to ensure that such employees receive user- and domain-centric instruction in practical terms on how to use the system, and also how it prioritises and makes recommendations on tasks and cases.

One of the great advantages of having humans and smart machines work alongside each other is that humans can confirm that an automated decision is ‘sensible’, that is, it is appropriate for the specific context and circumstances at hand. In a medical insurance coding case we researched, for example, the human coder audited the decision made by the system on how to code the patient’s treatment, for input into the records of the hospital and the insurance company. The individual was able to reverse it if the system erred in its assessment. In a policing case, a tool called ShotSpotter Connect made a recommendation about where the police officer should patrol and what to do while patrolling, but the officer ultimately made the decision based on his or her preference, and information that might not be available to the system.

In many work settings, the ‘right’ decision often depends on understanding the complex contingencies and contextual factors, which often cannot be fully captured in the data used for analysis. In such situations, it is far more difficult and riskier to build intelligent CMS that fully automate decisions without human review. In general, we believe the final output is usually better with the combination of human and machine expertise. That said, we also acknowledge there are many specialised situations where it is advantageous for fully automated decision-making. Examples include micro-decisions that need to be made in split seconds, or when the situation is very stable and well-characterised by available data and validated models. Even in these situations, it is necessary to design how humans, with the support of smart machines, can review, evaluate, or modify the automated decision-making approach, over time as conditions and context may change.

One advantage of these online CMS is that users, i.e., frontline workers and their supervisors, can work anywhere and anytime. All the resources required for getting work done are present in the online applications. This proved to be especially useful during the workplace restrictions resulting from Covid-19 countermeasures. At the same time, the positive aspects of this ‘freedom’ have countervailing impact, as everything needed for work is present at home.

Finally, employees using these systems need to accommodate the fact that their work is mediated and monitored by software. We found only moderate concerns about this among the individuals we interviewed. People involved in our case studies using these intelligent CMS say the latter improve their productivity, but admit to a certain relentlessness in their work, with a few confessing to a feeling of being “chained to the computer”, or complaining that “the work never stops”. We advise employers to mix this type of work with others involving social activities and non-computer work in order to make jobs more fulfilling, and avoid employee burn-out.

JOB ROLE-BASED ECOSYSTEM

We began the research project with a focus on the frontline workers using AI on the job, but realised quickly that a broader ecosystem was necessary in every case to create and maintain the AI-enabled work. But frontline employees are still important, of course. Those that we interviewed were not only positive about the smart machines they were working with, but also did not show any indication of fear about being replaced by them. Except for the few cases that involved full automation, workers believed that humans would remain

necessary in their job positions. They cited reasons such as the need for monitoring the machine’s outputs, handling unusual and non-standard situations, incorporating an understanding of context, interfacing with other internal or external people, big-picture thinking, and other intrinsically human capabilities. Even in the three examples involving full automation of a major portion of a production process, some human employees were still working in direct and indirect ways to execute the extended work process and monitor the automation.

These frontline workers genuinely appreciated what AI systems had done for their jobs. The systems had enabled them to work independently and often on their own schedules. AI had also made their work more intellectually stimulating. In many cases, it had dramatically improved their everyday productivity.

Most often, leaders and executive sponsors were the prime movers behind building the AI systems and kick-starting the job changes. The funding for this came from their budgets. They had a vision of how the new work processes would be performed, and sponsored the training and reskilling necessary for frontline personnel.

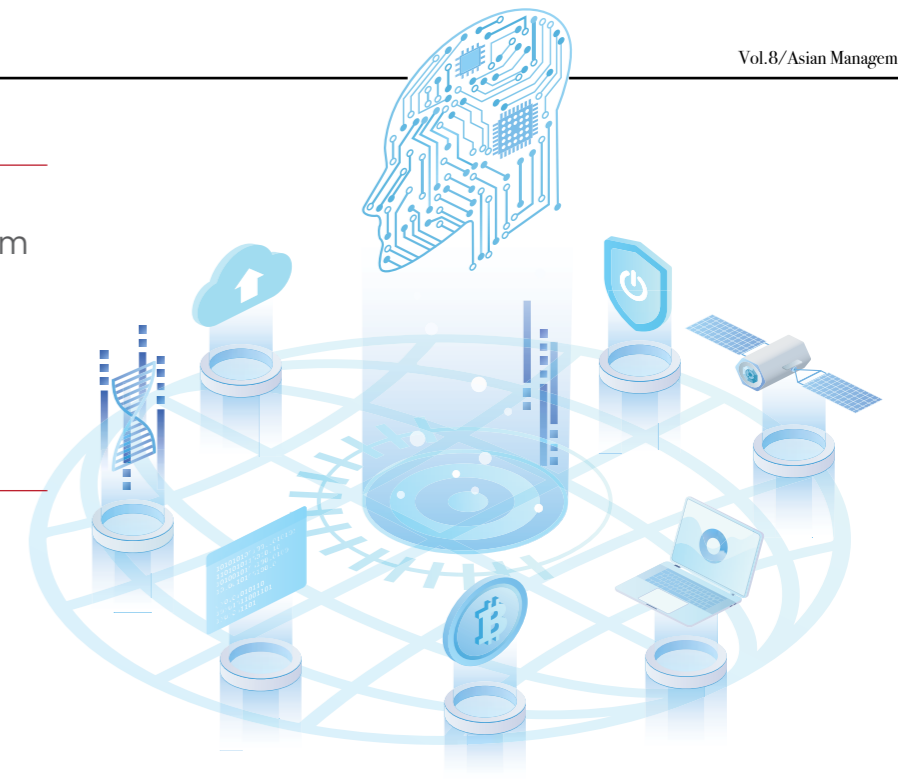
Frontline supervisors of work done collaboratively with AI also had an important role to play in the establishment of new workflows and patterns. They typically helped design the details of the work process, including how the work would be monitored and measured. They might also have pressed for improvements in the technology and become the primary interface with external vendors. In some cases, the AI system was their idea.

In many cases, substantial work on the AI deployments we examined was performed by IT professionals in the company, often together with an AI or data science group from their internal product development or innovation units. They were typically the ones to develop the applications and platforms that incorporate the AI or integrated vendor solutions into the company systems.

Additionally, vendors of AI systems or the platforms on which they run were critical for the successful deployment in specific company settings and in the overall marketplace.

One advantage of online, computer-based case management systems (CMS) is that users, i.e., frontline workers and their supervisors, can work anywhere and anytime.

New AI-based systems, their supporting platform and infrastructure, and their surrounding work processes, do not materialise easily or quickly.



They built and maintained the technology, were consulted on its implementation, and in some cases made us aware of their customers.

Finally, we uncovered several situations where a company’s customers or partners had a noticeable influence on the successful outcome. At the Jewel shopping mall in Singapore Changi Airport, the airport operator, which was a partner in developing Jewel, had a strong hand in designing and approving the new approach to security. In the case of language translation services for localising business content, a client even specified to the company the types of localised translations it preferred, which the ML system has learned to use.

Each of our case studies represents a complex collaboration amongst all or a subset of the job roles described above. This has an important implication. New AI-based systems, their supporting platform and infrastructure, and their surrounding work processes, do not materialise easily or quickly. Even with an agile approach to solution development and more standardised, commoditised, and rapidly improving vendor solutions, it is going to take time to orchestrate and align the deep and tight collaborations across the job role ecosystem. The process to arrive at the point where all aspects of the AI-enabled system and the intertwined work processes meet the company’s performance standards for even the initial phase of production deployment is meticulous and time-consuming. After that, there is still a need to continue system training as well as employee training, and provide feedback to improve the performance of these systems.

From these case studies and our broader industry interactions, we are starting to see a variety of new job specialisations

emerging across the job role ecosystem described here that are needed to make the implementation of AI systems successful. We are also seeing more examples of the hybridisation of business-related roles with IT and AI deep tech-related roles. This includes more examples of people with business backgrounds in IT and related tech roles (including the Chief Information Officer role), as well as people with deep tech (including AI and analytics) backgrounds being embedded into business units and other non-IT corporate groups. The need for companies to have more deep technical expertise in IT, AI, cybersecurity, and data protection continues to increase. At the same time, there is a parallel need for even more people in these same companies to step into these hybrid business-tech fusion roles.

Indeed, new AI developments are proceeding at breakneck speed. But bringing everything together across technology, people, and job roles in any real-world work setting is a very complex undertaking. Our advice is that any company interested in moving ahead with these new AI-enabled ways of doing work should begin by identifying, understanding, and engaging the complex ecosystem of stakeholders and participants in the new solution. The web of tasks and relationships needed for new AI-enabled work is complex enough that an organisation should use a structured project or product management methodology to manage the overall effort. They should also use both structured and unstructured communication tools that keep members of this job role ecosystem in frequent contact with one another.



AUTHORS' ASSESSMENT OF THE ROLE OF AI SYSTEM IN EACH CASE STUDY

	Primary role of AI system in this use case	Additional roles of AI system in this use case
Insurance and Financial Services Settings		
Banking transaction surveillance	Threat identification, analysis and intervention support	<ul style="list-style-type: none"> Filtering, prioritising vast amounts of information for human user to start with Supporting experienced employees to work more productively
Banking internal operations support	Making non-specialists into 'citizen' creators and users	<ul style="list-style-type: none"> Supporting experienced employees to work more productively
Banking wealth management advising	Motivating customers, prospects to engage in person	<ul style="list-style-type: none"> Filtering, prioritising vast amounts of information for human user to start with Supporting experienced employees to work more productively
Banking customer service support	Motivating, supporting customers to engage digitally	<ul style="list-style-type: none"> Supporting experienced employees to work more productively
Insurance underwriting	Supporting experienced employees to work more productively	Nil
Medical insurance coding	Supporting experienced employees to work more productively	Nil
Information-Oriented Service Work (Multiple Industries)—Language-focused AI applications		
Legal services due diligence	Filtering, prioritising vast amounts of information for human user to start with	<ul style="list-style-type: none"> Supporting experienced employees to work more productively
Software firm written content creation	Guiding less experienced employees on what to do	<ul style="list-style-type: none"> Supporting experienced employees to work more productively
Language translation services	Supporting experienced employees to work more productively	Nil
Information-Oriented Service Work (Multiple Industries)—Data-focused AI applications (and some also Language-Focused)		
Cybersecurity managed services	Threat identification, analysis and intervention support	<ul style="list-style-type: none"> Filtering, prioritising vast amounts of information for human user to start with Supporting experienced employees to work more productively
Grocery store chain analytics	Making non-specialists into 'citizen' creators and users	<ul style="list-style-type: none"> Guiding less experienced employees on what to do Supporting experienced employees to work more productively
Advertising services, media buying	Making non-specialists into 'citizen' creators and users	<ul style="list-style-type: none"> Supporting experienced employees to work more productively
Online food platform market and sales	Guiding less experienced employees on what to do	<ul style="list-style-type: none"> Supporting experienced employees to work more productively
University financial donations	Motivating customers, prospects to engage in person	<ul style="list-style-type: none"> Supporting experienced employees to work more productively
Healthcare Settings		
Online consultations with GP	Remote situational assessment of physical situations	<ul style="list-style-type: none"> Threat identification, analysis and intervention support Motivating, supporting customers to engage digitally Supporting experienced employees to work more productively
Dermatologist medical clinic	Remote situational assessment of physical situations	<ul style="list-style-type: none"> Threat identification, analysis and intervention support Guiding less experienced employees on what to do Supporting experienced employees to work more productively
Hospital pharmacy operations	Full automation of major portion of physical process	<ul style="list-style-type: none"> Supporting experienced employees to work more productively
Factory and Production Settings		
Highly automated factory	Full automation of major portion of physical process	<ul style="list-style-type: none"> Threat identification, analysis and intervention support Filtering, prioritising vast amounts of information for human user to start with Supporting experienced employees to work more productively
Machine shop producing bearings	Guiding less experienced employees on what to do	<ul style="list-style-type: none"> Filtering, prioritising vast amounts of information for human user to start with Supporting experienced employees to work more productively
Field Settings (Multiple Industries)		
Shopping centre facility operation	Threat identification, analysis and intervention support	<ul style="list-style-type: none"> Remote situational assessment of physical situations Filtering, prioritising vast amounts of information for human user to start with Guiding less experienced employees on what to do Supporting experienced employees to work more productively
Police patrolling	Threat identification, analysis and intervention support	<ul style="list-style-type: none"> Remote situational assessment of physical situations Filtering, prioritising vast amounts of information for human user to start with Supporting experienced employees to work more productively
Weeding of vegetable crops	Full automation of major portion of physical process	<ul style="list-style-type: none"> Remote situational assessment of physical situations Supporting experienced employees to work more productively
Electricity and gas utility safety	Threat identification, analysis and intervention support	<ul style="list-style-type: none"> Guiding less experienced employees on what to do Supporting experienced employees to work more productively
Commuter rail maintenance	Threat identification, analysis and intervention support	<ul style="list-style-type: none"> Guiding less experienced employees on what to do Supporting experienced employees to work more productively

TABLE 1

As a final observation on the relationship between humans and smart machines, if you are worried about the impact of AI on jobs, it should be good news that so many different types of people and job roles are required to plan, prepare for, build, operate, and continuously improve these AI systems. Even as AI automates some tasks entirely and others partially, there are plenty of new jobs and remaining tasks for humans to do.

What to expect in Southeast Asia

Of the 24 case studies, four were from Southeast Asia: three were located in Singapore and one in Indonesia, indicating that successful AI applications are already occurring within some local companies in the region. Consulting firm Kearney recently reported that AI adoption in Southeast Asia is still in the early part of the curve, noting that “the benefits of AI are clear, yet the adoption rate says otherwise: more than 80 percent of the region is still in the early stages of adoption”. It reported that only 30 percent of companies it surveyed were already developing or just starting to invest in AI capabilities. About 50 percent were piloting some AI initiatives. Only 15 percent were in advanced stages of AI implementation and this was typically in more service-oriented sectors. Over 80 percent were only devoting less than 0.5 percent of their revenues to embedding AI solutions into their operations.²

The Kearney report highlights that this situation of a relatively low adoption rate in the region is improving. According to the report, the region’s top five economic sectors—manufacturing, retail and hospitality, agriculture, healthcare, and government (including safety, security, and smart cities)—will especially benefit from increasing AI usage to drive strong overall impact. It can lead to a 10 to 18 percent gross domestic product uplift across Southeast Asia by 2030, equivalent to nearly US\$1 trillion.

In short, this means that over the next five to 10 years, we will see a lot more of everything described in our portfolio of case studies across Southeast Asia, especially in the six largest economies: Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam. It also means that those in the region leading or managing their company efforts to plan, deploy, and operate AI-enabled systems would benefit from paying attention to our insights.

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