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AI Adoption Strategies

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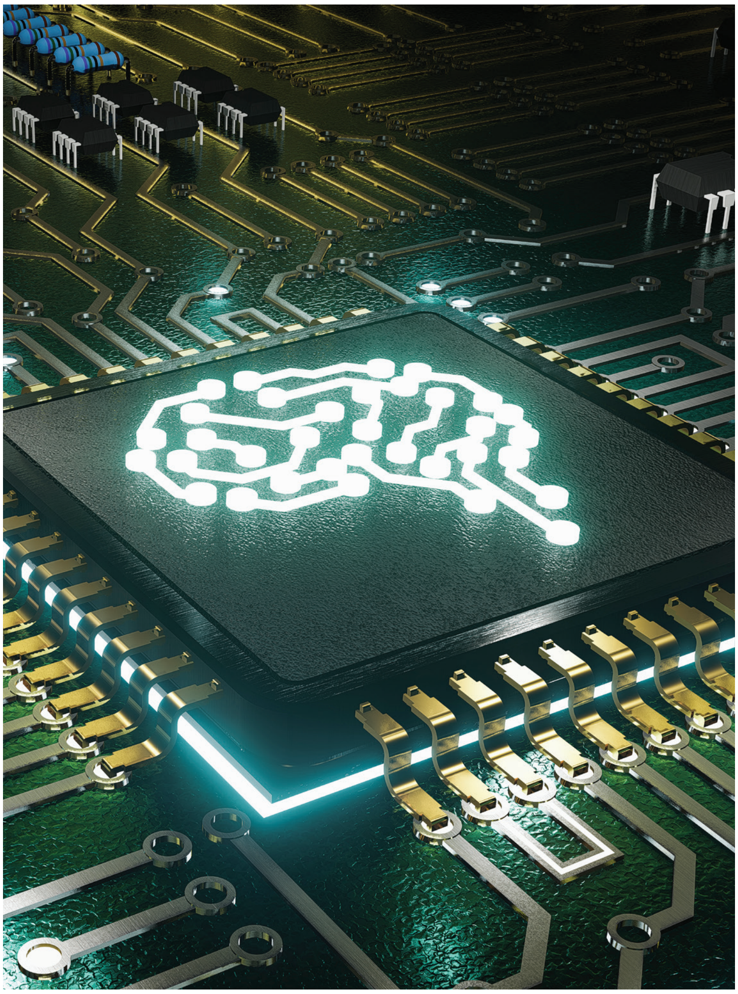

INTRODUCTION

Artificial Intelligence (AI) is now well-established as a transformative technology across various sectors of industry, from retail and manufacturing to transport, as well as in government and in scientific research. This paper examines the factors that influence adoption of AI in industry and government, and the opportunities and risks that such adoption will entail.

The transformative impact of AI comes from both its effect on intelligent decision making and predictions as well as from its facilitation of greater automation. While increased automation has been a key component of technological progress since the industrial revolution,[1] AI and Machine Learning (ML) techniques promise far greater automation than before. Automation can bring about lower costs and faster turnaround time on projects as well as free up human time for tasks that are less amenable to automation. The effort exerted towards automation can also identify bottlenecks in a project which cause friction and reduce efficiency.

Intelligence is an area where the contributions of AI as a technology are unique. Such intelligence currently depends on the large volume of data collected,[2] and affords greater insight into operational inefficiencies, a more holistic perspective of an enterprise and its market, and predicted growth opportunities. While there are many aspects of intelligence, in this report we focus on *prediction*, as it is more well-developed and of immediate relevance to organizations. Intelligence, in the form of prediction, provides unprecedented capabilities for organizations to monitor and improve processes that lead to higher productivity, efficiency, revenues, profits, and value. One of the relevant technology paradigms for organizational AI adoption is cross-enterprise AI, which links functional silos in an organization and improves cross-functional processes to derive insight. Unlike predictive analytics, which was the mainstay of prediction in the latter half of the 20th century and early 21st century, AI techniques offer orders of magnitude more predictive power using advanced statistical techniques, linked data from multiple sources as well as modelling of the organization, its decisions, and dynamic interactions with its markets or constituents.

To be sure, the adoption of AI also carries with it significant concerns, particularly with regard to automation and privacy. There is a risk that automation, if implemented indiscriminately, leads to significant job losses and increased fragility and higher single points of failure.

This paper proceeds as follows. Section 2 reviews the general technological landscape of AI. We then consider several models of technological adoption of AI in section 3. Section 4 examines concrete use cases from industry and government. Section 5 concludes with our key recommendations regarding AI adoption within government and private industry.

LANDSCAPE

Understanding the contextual landscape around AI is key to utilizing existing and emerging adoption frameworks for organizations. While the consensus is that AI adoption is on the rise and that organizations should adopt AI sooner rather than later,[3] there is no viable “one-size-fits-all” approach to AI adoption. In this section, we give an overview based on existing work of the AI landscape. We also discuss the capabilities, benefits, and transformative impact that AI affords as well as concerns about privacy infringement and unemployment.

As digitization sweeps across industries and governments, a shift from institutions to individuals follows in its wake. Consumers are empowered with choices and information about products, prices, and services, while social media provides scale to people’s opinions. Traditional industrial-era competitive advantages of scale, capital intensity, reputation, and relationships erode, and force competition on price, enriched customer experiences, and fulfillment immediacy. Thus, organizations require far greater operational agility,[4] which AI can provide.

AI is a general-purpose technology, such as the steam engine, electricity, microprocessor, and the Internet. Such technologies drive waves of change and innovation[5] and enable successive developments of new innovations and transformation of business and operating models. Following are two key aspects of any general-purpose technology: (i) it has a fundamental effect on every aspect of society; and (ii) it increases effectiveness as it drives down the cost of a key commodity.

The steam engine linked distant regions of the world, facilitating trade while reducing the cost of transportation. Electricity, with the advent of the light bulb, shifted working hours and lifestyles while reducing the cost of power consumption. More recently, the microprocessor enabled the proliferation of mathematical computation while reducing its cost. The Internet enabled the scope of digitization to

1 Erik Brynjolfsson and Andrew McAfee, *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies* (WW Norton & Company, 2014).

2 Ajay Agrawal, Joshua Gans, and Avi Goldfarb, *Prediction Machines: The Simple Economics of Artificial Intelligence* (Harvard Business Review Press, 2018).

3 Jacques Bughin, “Wait-and-See Could Be a Costly AI Strategy,” *MIT Sloan Management Review*, 2017, https://sloanreview.mit.edu/article/wait-and-see-could-be-a-costly-ai-strategy/.

4 Karin Ahlbäck et al., “How to Create an Agile Organization,” 2017, https://www.mckinsey.com/business-functions/organization/our-insights/how-to-create-an-agile-organization.

5 Brynjolfsson and McAfee, *The Second Machine Age*.

spread throughout the world while dramatically reducing the cost of communication. Internet companies have changed expectations of individuals as consumers and citizens, producing pressures for competitive adaptation across business sectors.

In the case of AI, the effectiveness of prediction is rising dramatically as the cost is plummeting with the falling costs of its enabling technologies.[6] Prediction pervades our lives and activities in ways that people scarcely notice but nonetheless rely upon. Clear examples of this trend include embedded AI in consumer products such as driverless cars, smart speakers, and online searches.

When applied to commercial enterprises or organizations, the effects of AI profoundly impact institutional performance and society at large. Using internal and external data, organizations can process the proliferation of previously neglected data, enabling organizations to detect prediction drivers much more precisely, comprehensively, and reliably than before. Predictions driven by multidimensional data enable organizations to supplant narrow, unidimensional considerations (often within a single business function), or intuition with an understanding of the dynamic interactions that drive organizational performance. AI enables organizations to replace relatively static operating models with dynamic decisions and interactions with customers or citizens. It also enables organizations to take actions faster and more frequently by leveraging the recent explosion in data availability and advances in computational power at lower cost. For example, AI is driving significant improvement in business demand forecasts. This enables supply to be dynamically balanced with demand and leads to increased customer satisfaction and reduced inventory by having the right product on hand at the right place and right time.

Predictive government services are broad, ranging from sophisticated weather prediction models, traffic flow, and smart lighting to improved predictions of successful research and development investments to population health improvements from the discovery of new treatments and more precise matching of treatments to patient conditions.

While AI adoption by organizations is generally beneficial both for organizations and their employees, there are two areas that AI adopters should especially keep in mind: privacy and employment.

Privacy. Increased intelligence also makes it easier for privacy infringements to occur. The regulatory climate around privacy is expected to become more stringent with time as a consequence of tighter regulations, such as the European Union's General Data Protection Regulation (GDPR). In this regard, organizations should ensure that processes involving AI are compliant with privacy regulations. It is also important to consider data storage and access. Data is being heralded as the new oil,[7] with its value being derived from being the key input to AI/ML algorithms. Secure access and storage of such data should be a priority for organizations. Even so, as AI/ML technologies become more capable, data which was previously harmless could become valuable for prediction and detection, which in turn could compromise privacy. Organizations should thus weigh possible privacy tradeoffs against increasing value of data over time due to increased capabilities.

Employment. The risk to employment from automation is well-established.[8] Studies have shown that, for example, in the United States, up to 47 percent of jobs are at risk — particularly jobs that involve low creativity and high manual work, such as in transportation. Organizations adopting AI thus should aim to re-skill their workforce. Humans and machines are good at different things; current machine learning algorithms are often inadequate to deal with edge cases in decisionmaking, whereas humans are still better than machines at performing inference given little data. Human-in-the-loop systems will still be necessary; organizations should aim to complement human efforts by machines when adopting AI, which also creates job opportunities. This would involve skills training to understand the AI techniques being employed and how they fit into organizational decision making, to interpret the output of the algorithms, and to understand the possible biases and failure modes of the AI systems.

ADOPTION FRAMEWORKS

Adoption of a complex technology such as AI requires consideration from several viewpoints. Technology adoption by individuals and organizations is a well studied topic in the information systems' literature. Here we focus on technology adoption models for firms (see Tiago Oliveira and Maria Fraga Martins[9] for a review) such as the diffusion of innovation (DOI) model;[10] the technology, organization, and environment context (TOE) model;[11] or

6 Agrawal, Gans, and Goldfarb, *Prediction Machines*.

7 The Economist, "The World's Most Valuable Resource Is No Longer Oil, but Data," May 2017, https://www.economist.com/leaders/2017/05/06/the-worlds-most-valuable-resource-is-no-longer-oil-but-data.

8 Carl Benedikt Frey and Michael A Osborne, "The Future of Employment: How Susceptible Are Jobs to Computerisation?" *Technological Forecasting and Social Change* 114 (2017), pp. 254–80.

9 "Literature Review of Information Technology Adoption Models at Firm Level," *Electronic Journal of Information Systems Evaluation* 14, no. 1 (2011) p. 110.

10 Everett M Rogers, *Diffusion of Innovations* (Simon; Schuster, 2010).

11 Louis G Tornatzky, Mitchell Fleischer, and AK Chakrabarti, "The Processes of Technological Innovation (Issues in Organization and Management Series)" 10 (1990), p. 2013.

the benefits, organizational readiness, and external pressure (BOE) model.[12]

While these frameworks have a common ground, they focus on different facets of technology adoption problems. DOI describes the diffusion of technology, and the factors that influence it; thus, DOI describes primarily (though not exclusively) the temporal component — the when of technology adoption. The TOE model describes the factors for technological adoption, focusing on the external pressures (e.g. market forces and government regulation), organizational structures, and technological availability. By contrast, the BOE model combines the organization and technology context of TOE into organizational readiness and adds a perceived benefit factor for looking at adoption. Thus, these frameworks describe the why of technological adoption, along with organizational factors. This leaves open the how of adoption.

Below we consider these three lenses (when, why, and how) of technological adoption, starting with a review of how the BOE model fits the AI adoption approach, followed by our own contribution: the functionality, availability, complexity, cost (FACC) model which builds upon the DOI model. Finally, we discuss top down vs. bottom up and build vs. buy approaches for how AI adoption can take place in organizations. For all these frameworks, we undertake a qualitative, rather than quantitative, discussion of the factors influencing adoption.

BOE MODEL OF TECHNOLOGICAL ADOPTION

The BOE model was originally developed to understand the adoption of EDI (electronic data interchange) technology, but has since been used as a general technology adoption model. The BOE model comprises three factors: external pressure, organizational readiness, and perceived benefits (Figure 1).

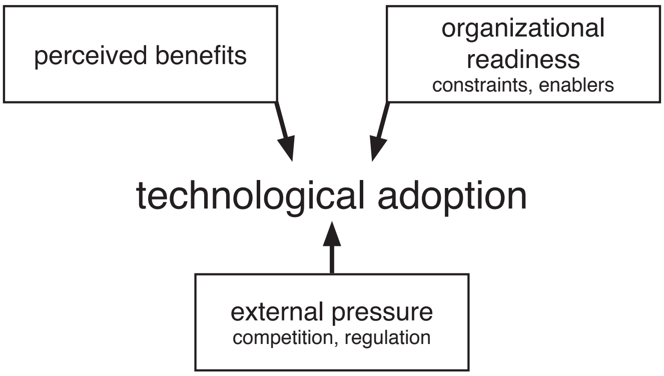

Figure 1. BOE model.

Perceived benefits. We discussed many of the perceived benefits of AI in section 2. AI has the benefit of boosting organizational productivity and efficiency. In the case of industries, this can lead to improved customer support with faster turnarounds as well as improved quality of service. For governments, AI can help develop predictive government services.

External pressure (competition). Early adoption of AI technologies confers competitive advantage to organizations.[13] In the case of industry, this can lead to increased efficiency, leading to greater manufacturing volume, process, and technological improvements.

For governments, AI offers a strategic advantage, particularly in cybersecurity and the military, strengthening a state's position in the international order. Like other enabling technologies such as electricity and the steam engine, the adoption of AI will lead to changes in global inter-nation power dynamics.[14] Various factors such as availability of a skilled workforce, the size of the AI industry, private-public sector partnerships, and regulatory frameworks will determine competitiveness of state actors.

External pressure (Government regulation). So far, the regulatory framework around AI is nascent. Most of the relevant regulations relate to privacy and ownership of personally identifiable information, the most recent example of that being the GDPR in Europe, which imposed opt-in requirements for some kinds of data, requirements for data portability, privacy by design, and extra-territorial applicability. While legislation is nascent, several countries have published their AI strategies (see Tim Dutton[15] for a review), which include provisions for development of AI. Most national strategies focus on increasing research and development in AI, as well as building relevant skills and speeding up digital transformation which is necessary for AI deployment. Some of them, such as the EU, are concerned about the socioeconomic impact of AI, particularly the future of employment.

In the short term future, regulation in AI will mostly be sector specific, such as those for drones and driverless cars. Other than such sector specific regulations, some issues that are of interest to regulators are those of transparency, algorithmic bias, and access to data.[16] Algorithmic bias refers

12 Charalambos L. Iacovou, Izak Benbasat, and Albert S. Dexter, "Electronic Data Interchange and Small Organizations: Adoption and Impact of Technology," *MIS Quarterly* 19, no. 4 (1995), pp. 465–85, http://www.jstor.org/stable/249629.

13 Sam Ransbotham et al., "Reshaping Business with Artificial Intelligence: Closing the Gap Between Ambition and Action," *MIT Sloan Management Review* 59, no. 1 (2017).

14 Michael C Horowitz et al., "Strategic Competition in an Era of Artificial Intelligence," 2018, https://www.cnas.org/publications/reports/strategic-competition-in-an-era-of-artificial-intelligence, Center for a New American Society.

15 "An Overview of National AI Strategies," June 2018, https://medium.com/politics-ai/an-overview-of-national-ai-strategies-2a70ec6edfd, *Politics + AI.*

16 UK House of Lords Select Committee on Artificial Intelligence, "AI in the UK: Ready, Willing and Able?" April 2018, https://publications.parliament.uk/pa/ld201719/ldselect/ldai/100/100.pdf.

to the bias in machine learning models, both from inherent model bias and bias originating from skewed training data. Particularly in the public sector and organizations using AI in applications which have an impact on an individual, we can expect guidelines, and later regulations, on fairness, accountability, and transparency requirements. Not all machine learning methods lend themselves well to being explicable, and there could be requirements to use more transparent methods. Greater deployment of AI systems will also lead to less decisionmaking by humans, though we expect regulations to ensure human-in-the-loop systems. Such automated decisionmaking raises issues of accountability for the decisions of the AI which are inadequately addressed by present legislation. While sector-specific approaches are being considered, such as for driverless cars, a uniform and consistent approach to the question of accountability is not in the near future.

Access to data is another issue that is mentioned in national AI strategy reports. Most AI/ML applications require large databases which may be prohibitively expensive to procure for SMEs. In the meanwhile, we foresee greater use of open data schemes by organizations as well as the creation of data marketplaces.

Various factors affect **organizational readiness**; we discuss the constraints and enablers that affect adoption of AI. These constraints and enablers are mostly the provision of essential resources (skills, financial and computational power, and data) for AI adoption that are available to an organization.

Organizational readiness (constraints). Organizational constraints such as culture or lack of skills and human resources to deploy AI will influence how they approach AI adoption.[17]

Industrial-era structures. The vast majority of organizations are structured according to principles first developed during the 19th century Industrial Revolution by Frederick Taylor to enable efficient operations at scale to service large and stable markets.[18] The organization, culture, and IT systems are structured in silos purposefully bounded in horizontal scope of responsibility and accountability and are designed to enable the vertical top-to-bottom flow of command and control throughout the organization. Incentives and Key Performance Indicators are aligned with this structure to focus individuals and departments on their segmented domains of functionality and accountability.[19]

With the disruption caused by digitization, these structures become significant constraints to the speed and agility required to serve the changed expectations of consumers and citizens. Even asset-heavy industries, long protected by significant barriers to entry by the need for significant capital investments, are impacted by digital disruption.[20]

Lack of skills. This is the most common constraint faced by small to medium scale organizations. Creating, deploying, maintaining, and interpreting AI/ML systems as well as the knowledge to integrate AI into existing business processes are skills that are in shortage.[21]

Budget constraints. Especially if there is already a lack of skills, budget constraints may prevent the upfront investment in hiring and necessary re-training.

Lack of direction or leadership awareness. A lack of understanding of the capabilities that AI brings, particularly in sectors which have so far used AI relatively less such as agriculture, can hinder the adoption of AI. A lack of awareness from the top management can result in AI adoption being limited to silos within the organization, and thus limiting effectiveness

Cultural Resistance. One of the main causes of friction in implementing large scale organizational changes like AI adoption is cultural resistance.[22] Particularly in the case of AI adoption, cooperation between groups in an organization is required to get the most benefits.

Data access. A lack of access to quality training data is detrimental to developing effective AI/ML applications within an organization. Especially when an organization is just starting AI adoption, it can be difficult to bootstrap AI applications without access to data, which in turn might require further investment to capture. This aspect of the landscape is changing and we consider this as an enabler in the next section.

Organizational readiness (enablers).

Access to technology. A large proportion of AI frameworks and libraries are developed as open-source projects. The availability of cutting-edge technologies as an open source

17 David Furlonger and Tom Austin, "What Cios Should Ask When Someone Pitches a Project That Uses AI," 2018, https://www.gartner.com/doc/3792879/cios-ask-pitches-project-uses; Randy Bean, Thomas. H Davenport, and New Vantage Partners, "Big Data Executive Survey," 2017, http://newvantage.com/wp-content/uploads/2017/01/Big-Data-Executive-Survey-2017-Executive-Summary.pdf.

18 Yves Cavarec and Brandon Fargis, "From Agile to Hyperagile: The Destination and the Journey," in *PMI® Global Congress 2016—EMEA* (Barcelona, Spain: Project Management Institute, 2016).

19 Michael Schrage and David Kiron, "Leading with Next-Generation Key Performance Indicators," *MIT Sloan Management Review and Google*, 2018, https://sloanreview.mit.edu/projects/leading-with-next-generation-key-performance-indicators/; "State of the Global Workplace," 2017.

20 Omar Abbosh et al., "The Big Squeeze: How Compression Threatens Old Industries," *MIT Sloan Management Review and Google*, 2017, https://sloanreview.mit.edu/article/the-big-squeeze-how-compression-threatens-old-industries/.

21 Will Markow et al., "The Quant Crunch: How the Demand for Data Science Skills Is Disrupting the Job Market," *Burning Glass Technologies, IBM, and Business Higher Education Forum*, 2017.

22 Bean, Davenport, and Partners, "Big Data Executive Survey."

facilitates their rapid diffusion and adoption by academia and organizations at all scales. This in turn fosters an ecosystem of free or affordable, easy to use, plug and play services built on top of these open source frameworks which can be used by organizations that lack the resources and skill sets to develop in-house solutions.

Data access. Most organizations have rich, yet incomplete and disorganized, data. Often, a mistaken assumption is that accurate data is a necessary prerequisite for AI adoption. While access to specialised data sources is still difficult and is a key constraint, there is an increasing availability of open data sets. Such datasets are typically released by governments in open data initiatives, and by non-profit organizations and researchers. The increasing availability of IT products can overcome incomplete and inaccessible data with data supplementation and algorithmic organization. It is also possible to obtain trained off-the-shelf AI models which can be used as a component in organizational AI capabilities.

Computing power. A decade ago, access to computational resources was an expensive process, usually requiring one to obtain dedicated servers. With the advent of cloud computing, access to computational power is affordable and convenient. This also allows organizations to only pay for the resources they use.

Access to complete AI solutions. The recent availability of highly functional cross-enterprise products is enabling organizations to adopt AI and realize its benefits within months while avoiding the traditional pitfalls of IT adoption, including lengthy and costly systems integration, organization-wide cultural changes, uncertain outcomes, and skills shortages.

FACC MODEL AND THE DIFFUSION OF INNOVATIONS

In this section, we consider the temporal component of AI adoption, and introduce a framework based on the well-known work on the diffusion of innovations,[23] as well as Mr. Wendler's over four decades of experience with adoptions of a many information technologies within a wide range of vertical industries, geographies, governments, and companies of varying size and competency. We therefore believe the model to be generally applicable to industry and government. The integration of these two constructs enables us to examine the context of users' adoption considerations at different stages of adoption as revealed by the different intersection profiles of the four factors.

23 Rogers, *Diffusion of Innovations*. The model proposed here draws on one of the co-author's (Steve Wendler's) more than four decades of experience working on the adoption of information technologies within a wide range of vertical industries, geographies, governments, and companies of varying size and competency.

There are four fundamental factors in the model that are considered by individuals and organizations when deciding to adopt emerging information technologies: functionality, availability, complexity, and cost (Figure 2).

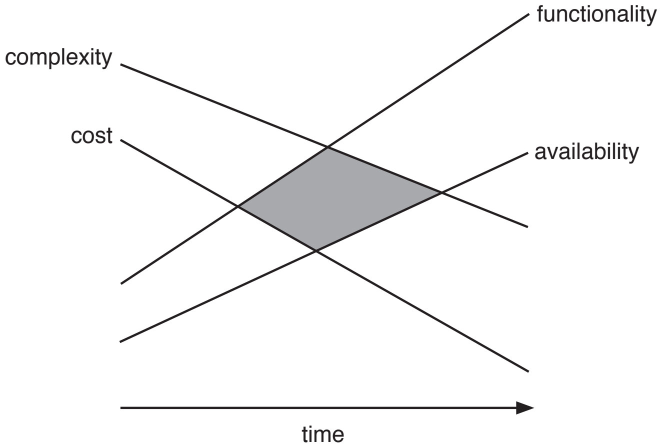

Figure 2. Graphical depiction of a two-dimensional projection of the FACC model of technology adoption. Shaded area is the optimal time for adoption for most organizations.

Functionality. Users understandably select a technology for which a problem is solved with varying degrees of functional completeness. When first introduced to the market, functionality is typically minimally viable in the form of limited-use tools, sparsely populated software libraries, stand-alone software applications, or other rudimentary forms. Over time, functionality expands with feedback from users, with advances of the core technology by researchers, and with the development of additional product features by providers. Tool sets or suites emerge; software libraries become densely populated; functional integration forms off-the-shelf packaged applications and finished solutions. Typically, this increase in functionality is modeled as a simple linear progression through time with a positive slope.

Availability. The availability of new technologies in consumable product form typically increases over time as well. Initially, the availability of products is limited to beta releases or early commercial versions from a small community of providers and then expands with increasing demand and with the competitive participation of more providers. We again choose to model this dynamic as a simple linear progression over time with a positive slope.

Complexity. The complexity of adoption is inversely related with varying degrees to its functionality and availability. Complexity is at its peak with initial product availability and falls over time as users gain experience and providers add functionality to simplify installation and maintenance.

The complexity of adoption varies significantly with the complexity of the technology itself, the requirement of integration of the technology with existing systems, the degree of impact on the adopting firms' workflows, the size and complexity of the adopting organization as training and education becomes prevalent, and more. We model these factors as a linear progression over time with a negative slope.

Cost. Like complexity, the cost of technology adoption is inversely related to its functionality and availability. The cost is typically at its peak with initial product releases and decreases over time as a growing community of providers compete on price, as economies of scale are engaged, as competing technologies become available, and other factors. Again, we choose to model this factor as a linear progression over time with a negative slope.

Of course, reality significantly departs from these simple linear progressions. All four factors are episodic and not continuous, and the slope varies significantly with events. Nonetheless, the combination of the factors serves as a useful reference in understanding organizations' adoption strategies.

At any point in time during a technology adoption, the intersection of the four factors forms different profiles which indicates the variation in adoption strategies and organizations' characteristics.

The adoption of emerging information technologies, including AI, has traditionally evolved as described by Rogers as the diffusion of innovations and the famous S curve, where the curve is segmented in three phases of experimentation, proliferation, and maturation. Each phase exhibits a different intersection of the four factors as well as different adoption methods and user characteristics.

Experimentation. The adoption of every emerging technology begins with the experimentation phase when early adopters seek to achieve the earliest and strongest value creation and/or competitive advantage. They exhibit high tolerance for a very limited supply of first-available, expensive, and relatively crude versions of products with limited functionality. Adoption is funded by budgets set aside for business growth and transformational investments. Adoption is undertaken with highly experienced personnel within carefully bounded laboratories frequently referred to as centres of excellence. There, isolated from organizations' core processes, staff are able to explore narrowly-defined, limited-impact, and tactical applications so as to accumulate skills in a low-risk environment.

Proliferation. As both providers and organizations move up the steep learning curve, mainstream technology adopters acquire the next available versions of products which have become more functionally complete and less complex to adopt. The risk of adoption is exhaustively explored by moderately skilled personnel, prices drop with increased competition, and the scope and scale of applications broadens from the periphery to core processes and operations. The leading edge of this period marks an inflection point of the favourable convergence of factors which engages "fast followers"[24] seeking proven value creation and/or moderate competitive advantage. The fast followers are accompanied by rapid expansion and pace of adoption which characterizes the proliferation phase.

Maturation. The maturation phase follows and is characterized by late adopters whose conservative adoption strategies wait until highly-functional products are widely available from a multitude of suppliers at reasonable prices and the complexities of adoption have been minimized. Typically, this is the phase in which substantial value creation may still be achieved in the form of reduced costs but competitive advantage is not probable.

As of this writing, we believe the four factors have favourably converged in the aggregation for the adoption of AI. Highly functional AI products have become recently available which enable organizations to achieve strategic and organization-wide value while avoiding the daunting complexities and exorbitant costs of traditional IT adoption. Thus, we believe the aggregate market for AI is at the cusp of entering the proliferation stage of organization-wide, strategic AI adoption; that this trend and will grow over the next decade as individual organizations' adoption strategies are executed.

Underlying and driving Rogers' model of the diffusion of innovations is the uniform and continuous transmission of innovations throughout any given network of users. While this has been demonstrated countless times over many decades, a more recent and disturbing phenomenon has appeared to disrupt this model. While innovative IT practices of industry leaders in many American industries have generated competitive advantage, they have remained proprietary and thus have not diffused to other industry participants per usual. This disruption of the flow of advantageous knowhow is correlated with the concentration of market power within those industries. This phenomenon, apparently achieved through the expanded use of trade secrets and employee non-compete agreements, has troubling implications for fairness of competition and indicates the need for consideration by public policy experts.[25]

24 Ransbotham et al., "Reshaping Business with Artificial Intelligence."

25 James E Bessen, "The Policy Challenge of Artificial Intelligence," *CPI Antitrust Chronicle*, June 2018, https://doi.org/10.2139/ssrn.3219887.

	build Extended time operation Can require hiring/developing scarce resources Systems integration is expensive/ time-consuming Multiple tools and technologies Uncertain outcomes	**buy** Shorter time-to-operation Leverage providersexpertise, experience, and staff Configurable use cases by industry Can avoid prerequisite organization-wide changes
top-down CEO & Board driven Centralized, Strategic Highest Business Value Directly drives revenues & profits Enterprise scale	**top-down build**	**top-down buy**
bottom-up Decentralized, Department-driven Tactical Lowest business value Indirect impact on revenues/profits Narrow scale	**bottom-up build**	**bottom-up buy**

Figure 3. Tradeoff matrix between top-down, bottom-up, build and buy approaches.

TOP-DOWN VS. BOTTOM-UP, BUY VS. BUILD

Top-down approach. The top-down approach is driven by boards and senior management or, in the case of government, top officials and ministers. Such an approach takes a holistic, strategic viewpoint on technology adoption and makes it an organization-wide priority. This approach takes into account desired outcomes for the commercial organization, such as improved customer relations, access to customer data, and greater throughput and/or productive capacity, and frequently delivers the highest value. For governments, desired outcomes include efficient and seamless access to services. Regardless, the top-down approach links them directly to high-level behaviour and process changes in the organization that are enabled by technology. This approach enables the establishment of organization-wide standards.

Several potential disadvantages of this approach can arise from the resources required by large complex organizations. Adoption strategies that require organization-wide cultural change can be both distracting and exhausting. Consider the sustained attention to multi-year coordination of hundreds or thousands of agile teams as proposed by Darrell K. Rigby, Jeff Sutherland, and Andy Noble.[26] This all-or-nothing approach often fails to account the complexity of large organizations and the resources required for a frictionless transition. Particularly for organizations that are new to the technology, a bottom-up approach can often be more practical, readily achievable, and carry less financial and reputational risk.

Given the general-purpose nature and predictive power of AI, its greatest value is achieved from adoptions which transform organization-wide operating models on a large scale. Given the recent availability of off-the-shelf products which enable organizations to seize the strategic benefits of AI on an incremental use case basis, all-or-nothing organization-wide cultural change can often be avoided.

Bottom-up approach. A bottom-up approach, in contrast, applies technology to the various components and processes in an organization and in a piecemeal manner, providing tactical competitive advantages and low business value. Such an approach has the benefit of relatively low risk and services can be transitioned one at a time. A drawback is that a bottom-up approach can take more time, which could lead to competitive disadvantage. Another disadvantage is that it usually involves technology adoption in silos, which prevents integration that is often the primary benefit of the technology.

Few information technologies are truly general-purpose and potentially transformative. The internet and AI are examples. While it is possible to adopt these technologies

26 "Agile at Scale," *Harvard Business Review*, May 2018, https://hbr.org/2018/05/agile-at-scale.

on a departmental or business unit basis, doing so will achieve incremental value relative to more transformational improvements to strategic and organization-wide operating models.

Build approach. Traditional build approaches develop custom solutions involving the hiring of specialized internal staff (such as data scientists), investing in training and tools and technology, or investing in elaborate IT systems integration projects that frequently consume years to produce uncertain or disappointing results. In late 2015, McKinsey Global Institute surveyed nearly a thousand C-suite executives and found that two-thirds of C-suite executives expect revenue and profit increases of 5 to 15 percent from digital initiatives. Simultaneously over half of C-suite executives believe they are realizing less than 20 percent of the expected value.[27] The advantage of the build approach is that it results in a custom, proprietary solution which can provide sustained competitive advantage, particularly if key personnel can be retained. In addition, in-depth in-house knowledge of the AI system provides resilience.

Buy Approach. The buy approach is typically engaged when commercially available products are available which partially or fully satisfy the functional requirements of the application. This approach has the major advantage of time-to-operation. Providers frequently have a library of templates and use cases that are readily available and configurable for selected industries. The buy approach also affords the opportunity to leverage the providers' expertise, experience, and staff. This is particularly valuable in the case of AI considering the current worldwide shortage of data scientists. The buy approach can enable organizations to achieve desired outcomes while avoiding a prerequisite organization-wide changes to culture and workflows thus allowing organizational change to occur at a designated pace.

USE CASES

In this section, we consider several use cases which explore how our adoption framework relates to existing instances of AI adoption. While we consider specific examples, our adoption framework is general.

AI ADOPTION IN UK GOVERNMENT

In this section we discuss the current state of the art in AI adoption in the UK government in relation to the adoption frameworks presented in the previous section.

In the UK, the government has recognized the importance of AI adoption, both in encouraging industry and in using AI to deliver better services to its citizens. In terms of the BOE model, the benefits of AI adoption in the UK, like for other governments, lies in building competitive advantage and skills in AI, which will play an important role in preparing society for the increased automation and skills displacement that is likely to occur as AI adoption gains pace. Other countries have also published AI strategies to increase investment and education in AI, as well as the use of AI in public services, which is an external pressure for nations to adopt AI.

In terms of organizational readiness, the UK is well-positioned to take advantage of its well-established service and technology sector to take a lead in AI adoption. It has committed to establishing the Government Office on Artificial Intelligence and a Centre for Data Ethics and Innovation alongside an AI Council, which will have members from academia, industry, and the public sector. The UK also has an established open data initiative[28] which is essential for promoting AI applications, particularly from SMEs and startups. Some cities have also established real-time data collection and availability on metrics such as traffic flow and crime. London has its own open data repository,[29] and Glasgow[30] is using technology, including AI, to transform into a smart city. Smart lighting and a unified operations centre, among other innovative efficiency gains, has given a return on investment of £144 million.[31]

Governments have different priorities compared to industry and other organizations. Its primary interest is the safety and security of its citizens as well as providing essential services. From the point of view of when to adopt (FACC model), governments should not be expected to adopt AI as quickly as commercial organizations. By their very nature, governments are risk-averse. Nevertheless, governments should start preparing for AI and developing AI strategies to be competitive in attracting talent, ensuring a sustainable adoption of AI, and building a strategic advantage in a key technology.[32] With regards to top-down vs. bottom-up and build vs. buy, we believe governments should utilise a combination of the approaches. In applications critical to security, governments should invest in in-house talent, if not to build, but at least to understand AI algorithms and frameworks. Strategic partnerships can be formed and incubators established to encourage growth of the AI sector. The UK has already set out a white paper on an AI Sector

27 Jacques Bughin, Andy Holley, and Anette Mellbye, "Cracking the Digital Code," September 2015, https://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/cracking-the-digital-code.

28 UK Government Open Data Service, https://data.gov.uk/.

29 London Datastore, https://data.london.gov.uk/.

30 Future City Glasgow (Smart City Programme), http://futurecity.glasgow.gov.uk.

31 UK Government Case Study, "Glasgow a World-Leading Smart City with Support from Innovate UK," November 2017, https://www.gov.uk/government/case-studies/glasgow-a-world-leading-smart-city-with-support-from-innovate-uk.

32 Horowitz et al., "Strategic Competition in an Era of Artificial Intelligence."

Deal[33] that recommends against the 'wait and see' approach, and recommends increasing investment in R&D, investing in STEM (science, technology, engineering, and mathematics) education, and a National Retraining Scheme that will support re-skilling people in new digital technologies. Enabling partnerships with industry with initiatives such as the GovTech Catalyst[34] challenge will also drive adoption of AI. With regard to the top-down vs. bottom-up approaches, we believe that for most governments, a top-down approach is better to drive the required adoption of AI. Without support from the highest echelons of government, it is not possible to derive the transformative benefits of AI in the public sector.

Data-driven policy is an area where we expect to see more investment in governments in the near future. In particular, linked datasets can offer insights driven by AI that can submit feedbacks to governments about policy implementations. This can lead to smaller cycles from policy draft to legislation and to implementation.

AI ADOPTION IN RETAIL, CONSUMER GOODS, AND EQUIPMENT RENTAL

AI is being applied to some of the most vexing business problems today and virtually all use cases involve prediction. In several sectors, machine learning is being applied to demand forecasting, store assortment optimization, delivery optimization, and sales optimization. We give a few examples from client work done by r4.

In one case, a regional beverages company with tens of thousands of vending machines deployed in the field exhibited the characteristics of an early adopter (organizational readiness). AI functionality at the time of the adoption in the mid-2000's was in the experimentation stage. Functionality was primitive relative to today's standards, and availability of hardware and software was extremely limited. Telemetry hardware was commercially unavailable, requiring custom design and manufacturing. The complexity of the integration of the hardware and software components was very high. The solution was essentially first-of-a-kind and the cost was very high. Nonetheless, the firm engaged in a top-down approach driven by executive management's quest for competitive advantage (perceived benefit). Machine learning was used to generate reliable recommendations for the right assortment at the stock-keeping unit (SKU) level for each of the machines – creating deep granular insights of the specific demand characteristics of the machines. Dynamic demand forecasting based on those local demand drivers then enabled the company to fulfill local demand (external pressure) in a more agile way, resulting in double-digit increases in sales and a shift of its delivery model from large, heavily stocked trucks to smaller trucks carrying the predicted replenishment stocks.

In the consumer packaged goods industry, technology adoption was significantly different given the progression of technologies and products from the experimentation to the proliferations stage in the roughly ten-year period following the previous example. In this case, an aggressive global hard-goods company, also employing a top-down approach, was driven by the pursuit of competitive advantage (perceived benefit, external pressure). But, they chose to buy rather than build. This approach was enabled by the commercial availability of a highly-functional AI, a software-as-a-service solution as well as the widespread commercial availability of open-source software and relatively low-cost and high-capacity clusters of computing power (organizational readiness). The highly-integrated nature of the AI solution avoided the need for custom design and manufacturing and extensive systems integration. This greatly reduced the complexity, cost, and time-to-adoption. This solution replaced a weeks-long, spreadsheet-based, and global demand forecast process primarily based on historical sales data with a continuously updated and refined demand forecast. The system currently generates specific SKU sales forecasts derived from the integration of actual demand data from retail outlets enabling better decisions and faster actions for each SKU, each channel, at each outlet. This precise and dynamic approach to demand forecasting resulted in a double-digit increase in forecast accuracy and is projected to enable major supply chain efficiencies of hundreds of millions of inventories.

In the construction rental equipment industry, sales prospect targeting has been optimized through the generation of prioritized sales opportunities. Machine learning was employed to analyze patterns and generate predicted revenue of each opportunity using multidimensional data consisting of the customers' needs, preferences, prior rental behaviour, proximity of competitors, competitors' available rental inventory (external pressure), nearby construction project starts, competitive pricing, and more. The results of the adoption were double-digit increases in sales and improved inventory utilization (perceived benefit). This use case was driven by the same four factors as the previous two examples. The approach was similar to the previous use case where the same highly-functional, commercially-available, and highly-integrated AI solution (organizational readiness) significantly lowered the complexity of adoption. Complexity was further reduced by the distribution of the generated opportunities to the sales representatives through the company's existing customer relationship management system. All three examples demonstrate the applicability of the framework with variations of industries and technological maturity.

33 UK Government Policy Paper, "AI Sector Deal," April 2018, https://www.gov.uk/government/publications/artificial-intelligence-sector-deal/ai-sector-deal.

34 UK Government Guidance - the GovTech challenge process, https://www.gov.uk/guidance/the-govtech-catalyst-challenge-process.

CONCLUSION: RECOMMENDATIONS FOR ACTION

In this article, we described various adoption strategies for AI along with their respective advantages and disadvantages using existing adoption frameworks. We also introduced a general technological adoption framework that builds on existing theories of technological diffusion. Overall, we believe organizations should adopt AI sooner rather than later, while keeping in mind their requirements and the concerns around adoption that we highlighted. We conclude with recommendations for AI adoption for industry and government. While there are significant variations by industry, geography, competitive intensity, organization size, competence, and other factors, we believe we have provided representative, if not exhaustive, demonstration of the general applicability of the discussed AI adoption frameworks to industry and government.

INDUSTRY

1. **Aggressively adopt AI.** For those pressured by strategic and urgent competitive threats, hesitation is not an option. CPG, retail, and media are experiencing intense pressure from the tech giants and early adopters. In other industries with different dynamics, sometimes waiting can be a winning strategy. However, depending on the intensity of the competition, this could be costly, particularly when implementing AI. Surveys conducted by the consulting firm McKinsey & Co. suggest that the competitive intensity of implementing AI is accelerating. Early adopters in retail, transportation, financial services, and manufacturing are expecting 20 percent higher profit growth, with roughly half of that coming at the expense of their competitors. McKinsey argues that the longer firms hesitate, the more likely the revenue and profit gains from AI implementation will dissipate. They advise the decisive rejection of the wait-and-see approach to AI and the pursuit of implementation at scale as soon as feasible to share in the estimated $1 trillion shift in profits from slower-moving companies.35
2. **Prefer buy over build.** The availability of AI commercial-off-the-shelf products that organizations could buy to fulfill organization-wide strategies did not exist until recently. Implementations of AI on a large scale (excluding the digital-native technology giants) have been either extensive and expensive custom-built internal projects or systems integration projects. Commensurate with the early stages of AI, offerings labeled as enterprise AI for businesses and government have been little early versions of tools and software libraries targeted at application developers for the creation of narrowly-focused, tactical applications isolated from core, cross-functional processes that directly interface with markets, customers or constituents.

   However, a new category of cross-enterprise AI has emerged with several providers offering full suites AI functionality, enabling organizations to avoid the pitfalls of internal custom-built applications. The decision to buy AI products is particularly relevant given the projected worldwide shortage of data scientists with advanced degrees and several years of work experience.[36]
3. **Employ the top-down approach.** Organizations continue to struggle to fulfill the ambitions of senior executives to transform from industrial operations to digital operations at scale. Now that highly functional commercial-off-the-shelf products are becoming available that strategically apply AI to core and cross-functional processes, these ambitions can be achieved. Typically, these products are operational within a year and enable significant progress toward organizational goals with relatively modest investments and without prerequisite organization-wide changes to culture, established infrastructure of IT systems, or workflows.

GOVERNMENT

1. **Building a skilled workforce.** The advent of AI is going to change the nature of employment in multiple sectors. Particularly, manual and routine jobs are susceptible to automation. Alongside, new jobs will be created which will require a skilled workforce adept at understanding and working with automation. To take advantage of the opportunities that AI offers, and to offset the negative impact of job displacement, governments should invest in building a skilled workforce and education at all levels. Having a skilled workforce also gives greater strategic autonomy to governments.
2. **Form strategic industry partnerships.** Governments should foster an environment conducive to AI startups, and form partnerships with industry for public sector projects. Such partnerships can be mutually beneficial and enable faster adoption of AI by governments.
3. **Open data sets.** Governments collect a wealth of data on their citizens and the services they provide, such as in employment, crime, demographic data, traffic flows, and health. Currently, very few governments have open

35 Bughin, "Wait-and-See Could Be a Costly AI Strategy."

36 Markow et al., "The Quant Crunch."

data initiatives. Such initiatives to promote open data allow startups and established players to employ AI/ML techniques to deliver insight. While data is vital to the functioning of an AI-enabled government, it often lacks in-house skills to make use of that. Making non-sensitive data open to the public invites participation from multiple stakeholders, as well as democratizing access to valuable data, which can help startups and SMEs.

4. **Establish entities to oversee AI adoption.** Establishment of entities like the AI Council and the Government Office for AI in the UK are a key step in ensuring successful adoption of AI by governments and societies. Such entities would be tasked with the development of guidelines and ethical codes of conduct for industry to ensure that the manifold benefits of AI are used for public good. These would also be proactive in monitoring AI adoption and raising awareness of any issues.

5. **Engage public and awareness campaigns.** Finally, governments have the duty to engage the public in its AI adoption strategy. As mentioned in Landscape, the adoption of AI carries with it concerns such as those of privacy and jobs displacement due to automation. It is thus vital that governments communicate clearly to their citizens the impact that AI adoption might have on them as individuals, and on society as a whole. Any adoption of AI that has privacy concerns or risks a rise in unemployment should be discussed with relevant stakeholders, the industry, workers, and the general public.

6. **Selectively adopt AI.** Governments have different requirements from industries and provide a wide gamut of services to their citizens. We recommend that governments adopt AI in selected departments where privacy risks are low, such as in tax fraud detection or traffic flow prediction by cities. Overall, governments should also develop in-house skills to develop and maintain their own AI applications, particularly where data privacy is a concern, and where AI becomes part of critical national infrastructure.

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