The Digitalisation of Science, Technology and Innovation

KEY DEVELOPMENTS AND POLICIES

EXTENDED SUMMARY

OECD

THE DIGITALISATION OF SCIENCE, TECHNOLOGY AND INNOVATION

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Extended Summary

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Acronyms, abbreviations and units of measure

3D	Three-dimensional
AI	Artificial intelligence
AR	Augmented reality
DLT	Distributed ledger technology
DNA	Deoxyribonucleic acid
DSIP	Digital science and innovation policy
ETIS	Estonian Research Information System
GDP	Gross domestic product
HEI	Higher education institution
HPC	High-performance computing
ICT	Information and communication technology
IP	Intellectual property
ML	Machine learning
MOOC	Massive open online course
NNMI	National Network for Manufacturing Innovation (United States)
OA	Open access
OECD	Organisation for Economic Co-operation and Development
R&D	Research and Development
SMEs	Small and medium-sized enterprises
SOFA	Self-Organized Funding Allocation
STI	Science, technology and innovation
US	United States
USD	United States dollar
VR	Virtual reality

Executive Summary

This report examines digitalisation's effects on science, technology and innovation and the associated consequences for policy. Digitalisation today is the most significant vector of innovation in firms, science and governments. If properly harnessed, digital technologies could advance science, raise living standards, help protect the natural environment and improve policymaking itself.

Digitalisation and science

Digitalisation is bringing change to all parts of science, from agenda setting, to experimentation, knowledge sharing and public engagement. To achieve the promise of open science research budgets need to account for the increasing costs of managing data. Greater policy coherence and trust between research data communities are needed to increase sharing of public research data across borders. Co-operation is required to build and provide access to cyber-infrastructure internationally. And open access (OA) publication requires incentives for OA that match mandates coming from research funders.

Governments should also support platform technologies for science, such as distributed research and development networks, and storage for digital/genetic data. Room exists to better exploit advanced digital technologies in science. Artificial intelligence (AI) can increase productivity in science, at a time when research productivity may be falling. But policies are needed on high-performance computing, skills, and access to data (such as standardisation for machine readability of scientific datasets). AI in science also raises novel policy issues: for instance, will intellectual property systems need adjustment as invention by machines expands?

Realising the untapped potential of digital technology in policy

Digital technology could support policymaking for science and innovation in novel ways. Few governments have experimented with the opportunities available. Examples include: self-organised funding allocation; using collective intelligence through digitally enabled prediction markets and machine-crowd combinations; developing blockchain applications in science; and, using social media to help spread innovation.

Digitalisation and innovation in firms

As businesses innovate with data, new policy issues are likely to arise. For instance, restricting cross-border data flows can raise firms' costs of doing business, especially for small and medium-sized enterprises (SMEs). Decisions may soon be required on as yet unanswered policy questions: for example, should data transmitted in value chains be protected from sale to third parties?

AI is finding applications in most industrial activities. But firms with large volumes of data may not have the in-house skills to analyse it fully. Governments can work with stakeholders to develop voluntary model agreements and programmes for trusted data sharing. For more general AI applications, governments can also promote open data initiatives and data trusts and ensure that public data exist in machine-readable formats.

Effective sectoral support is also needed, for instance through roadmaps or sectoral plans, prepared with industry and social partners. Policy should also facilitate collaboration for innovation, for instance, by digitally enabled crowdsourcing and open challenges.

Even in the most advanced economies, the diffusion of advanced digital technologies needs to accelerate. Institutions for technology diffusion – such as applied technology centres – can be effective, and should be empowered to take longer-term perspectives, rather than prioritising short-term revenue generation. To help diffuse digital technology to SMEs governments can: systematise key information for SMEs; develop information on the expected return on investments in new technologies, and on complementary process changes within firms; provide signposts to reliable sources of SME-specific expertise, along with facilities where SMEs can test varieties and novel combinations of equipment.

Developing digital skills

Occupational titles like "industrial data scientist" and "bioinformatics scientist" are recent and reflect a pace of technological change that is contributing to shortages of digital skills. Entirely new fields of tuition are needed, such as dedicated programmes for the autonomous vehicle industry. Existing curricula may also need to change. Many schools barely teach data analysis, and more multidisciplinary education is needed.

Measures are required to address the fact that in many countries, in some subjects, such as AI, male students far outnumber female students. Digital technologies such as virtual reality could also facilitate novel forms of skills development, as is happening in industry.

Committing to public sector research

Publically financed basic research has often been critical to advances in digital technology. A recent levelling off – and in certain cases decline – in government support for research in some major economies is a concern. The complexity of some emerging digitally based technologies exceeds the research capacities of even the largest individual firms. This necessitates a spectrum of public-private research partnerships. Interdisciplinary research is also essential. Policies on hiring, promotion and tenure, and funding systems that privilege traditional disciplines, may impede interdisciplinary research. Scientists working at the interface between disciplines need to know that opportunities for tenure are not jeopardised by doing so.

Building expertise in government

Without governments fully understanding technologies and sectors, opportunities to benefit from digital technologies might be lost. Calls to regulate AI highlight the need for expertise in government, such that any regulation of this fast-evolving technology does more good than harm. Technical expertise in government will also help to avoid unrealistic expectations about new technologies. As a wide array of critical systems become more complex, mediated and interlinked by code, governments also need improved understanding of complex systems. And as innovation agendas quickly evolve, governments also need to be flexible and alert to change.

To use digital science and innovation policy (DSIP) systems to help formulate and deliver science and innovation policy, governments must: ensure the interoperability of the data sets involved; prevent misuses of DSIP systems in research assessments; and, manage the roles of non-government actors, particularly the private sector, in DSIP systems.

The digitalisation of science, technology and innovation: Key developments and policies

Introduction

In 2015, in their joint declaration (OECD, 2015), ministers from OECD countries and partner economies, at the OECD Ministerial Meeting in Daejeon (Korea), recognised that digital technologies are revolutionising science, technology and innovation (STI). The ministers asked the OECD to monitor this transformation.

During 2017 and 2018, the OECD's "Going Digital" project comprehensively examined digital technology's economic and social impacts. The resulting report, *Going Digital: Shaping Policies, Improving Lives* (OECD, 2019a), presents a strategy for policy making in the digital age. Complementing that report, this publication examines digitalisation's effects on STI and the associated consequences for policy. It draws mainly on work performed under the aegis of the OECD's Committee for Scientific and Technological Policy.

Why does digitalisation matter?

The importance of digitalisation in STI is hard to overstate. As the technology commentator Kevin Kelly observed, "This is the first and only time the planet will get wired up into a global network" (Kelly, 2013). Furthermore, digitalisation's impacts are just beginning. Around a century passed before the full effects of earlier technology revolutions, linked to steam and electricity, became clear. By those standards, the digital revolution has generations to go.

Digitalisation is ubiquitous in STI in part because its effects are both microscopic and macroscopic. At the microscopic level, for example, researchers recently stored 200 megabytes of high-definition video and books in deoxyribonucleic acid (DNA). At the macroscopic level, new digital technology means that a standard 10-pound satellite can capture better images of any point on Earth than a 900-pound satellite 20 years ago (Metz, 2019).

If anything, this publication illustrates that digitalisation's effects are deeper than most media reports reflect. Areas of research not traditionally associated with digitalisation, and on which advanced economies depend, from materials science to biology, are increasingly digital in character. At the same time, digital technology is changing the processes of science and enlarging its scope. For example, digitalisation is making science more collaborative and networked. In 2015, for instance, researchers working on the Large Hadron Collider published a paper with a record-breaking 5 154 authors. Many of the processes and outputs of science also improve digital technology. For example, physicists designing the Large Hadron Collider federated computing systems at hundreds of sites to analyse petabytes of data, further developing grid computing.

In STI, the pace of change brought by digitalisation is also striking. In all likelihood, no one foresaw in 2007 that ten years later more than a million people would be working in companies labelling and annotating data and images for machine-learning systems (Hutson, 2017). Similarly, until recently, only a few devotees understood distributed ledger technologies (DLTs), much less the possibility of combining artificial intelligence (AI) and DLTs such that each amplifies the other (Corea, 2017).

Digitalisation is also facilitating convergence among technologies, a hallmark of innovation. Digital technologies can be combined – more easily than many other technologies – because of the shared numerical basis of different digital devices. Miniaturisation, which digital technology propels, likewise facilitates convergence. For instance, millimetre-sized computers could become common in the next decade (Biles, 28 September 2018). Such devices are likely to converge with medical technologies, for example in monitoring disease processes from inside the body.

The broader context in which science, technology and innovation are digitalising

The digitalisation of STI is directly relevant to many important short- and long-term policy challenges. Over recent decades, for example, labour productivity growth has declined in many OECD countries. Efficiency-enhancing production technologies and organisational changes are necessary to counter this decline. Rapid population ageing means that raising labour productivity is ever more urgent; the dependency ratio in OECD countries is set to double over the next 35 years. In addition to increasing performance in many tasks, digital technology contributes to productivity in part by making the mixing and recombining of ideas easier, which facilitates innovation. Some evidence even suggests that innovation increasingly occurs by combining existing ideas rather than by forming new ones (Youn et al., 2015).

A related and worrying possibility is that the productivity of science might be faltering. Some scholars claim that science is becoming less productive. They argue, variously, that the low-hanging fruits of knowledge have now been picked, that experiments are becoming more costly, and that science must increasingly be done across complex boundaries between a growing number of disciplines. Scientists are also flooded with data and information. The average scientist reads about 250 papers a year, but more than 26 million peer-reviewed papers exist in biomedical science alone.

Any slowdown would have serious implications for growth. Increased funding would be needed to maintain discovery at previous levels and to seed innovations and raise economic productivity. Any boost to research productivity spurred by digital technology, from open science to the wider use of AI, could be of structural importance.

If deployed effectively, digitalisation could also help accelerate science and technology's ability to resolve global challenges. Environmental challenges include a warming atmosphere, loss of biodiversity, depleted topsoil and water scarcity. Health challenges include threats of disease – from multidrug-resistant bacteria to new pandemics. Breakthroughs in science and technology are necessary to address such challenges, and to do so cost-effectively.

This report also examines policy challenges created by digital technology itself. For example, owing to digitalisation, technology choice may be becoming more complex, even for large firms. One eminent venture capitalist recently wrote:

> *"Many of my friends at big companies tell me that 'what is 5G ?' floats around a lot of corporate headquarters almost as much as 'what is machine learning?'" (Evans, 2019).*

Digitalisation might also widen capability gaps in science across countries, owing to the uneven distribution of complementary assets such as computational resources, human capital and data access. Issues such as how to cope with so-called "predatory" online science journals, and how to keep personal research data anonymous, illustrate that new (and useful) applications of digital technology can generate new policy concerns.

Digitalisation also creates the need for new thinking about institutions and norms, both public and private. For example, in the public sector, governments in a number of countries are considering whether commissions for AI and robotics might be necessary. Similarly, in the private sector, as AI voice assistants become increasingly lifelike, firms must decide if customers should have the right to know that they are talking with machines. Rapid developments in digital technology may also require that regulatory processes become more anticipatory.
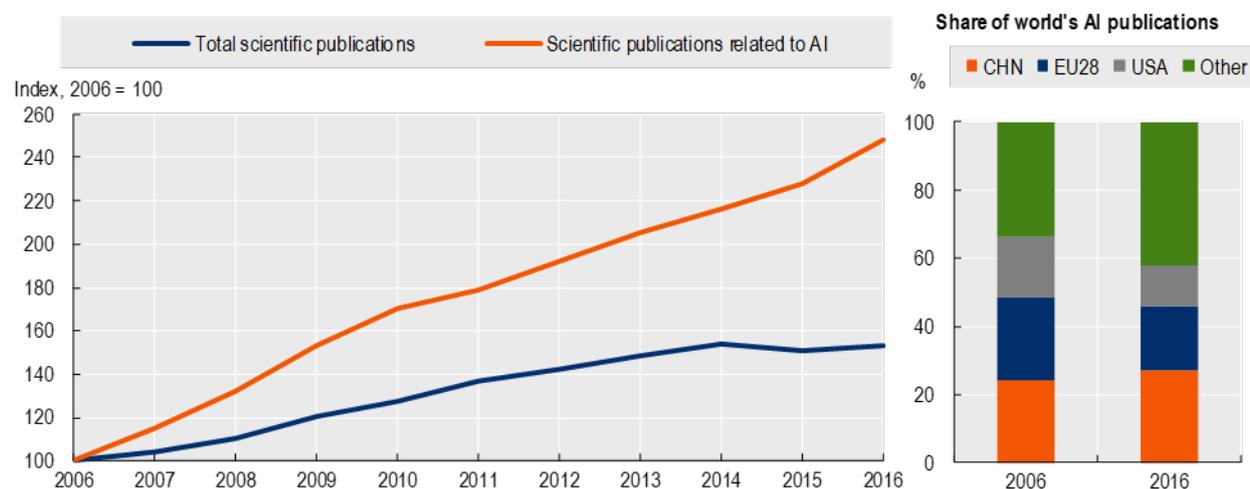
Measuring the digitalisation of science and innovation

The report addresses measurement challenges and provides statistics on some key trends in the digitalisation of science and innovation. Data are reported on four broad dimensions of the digital transformation of science: i) adoption of facilitating digital practices and tools; ii) access to digitised scientific outputs, especially publications, data and computer code; iii) use and further development of advanced digital procedures to make research more data-driven; and iv) communication of scientists' work and how this influences the way scientists are rewarded.

From 2006 to 2016, the annual volume of AI-related publications grew by 150%, compared to 50% for indexed scientific publications overall (Figure 1). The People's Republic of China (hereafter "China") is now the largest producer of AI-related science, in terms of publications. Public funding of science relating to AI is growing significantly, with a spate of recent policy and funding announcements. However, comparisons across countries are difficult because AI does not fit into pre-established taxonomies of research and development (R&D) funding. Indeed, available data systems are ill equipped to address queries about subject areas supported by publicly funded research. Addressing this shortcoming is an OECD priority.

Figure 1. Trends in scientific publishing related to AI, 2006-16

Index of publication counts

Source: OECD (2019b), *Measuring the Digital Transformation: A Roadmap for the Future*, https://doi.org/10.1787/9789264311992-en.

StatLink 🖏📑 https://doi.org/10.1787/888934075735

Overall, while digital activity in science is pervasive, there is considerable room to better exploit the potential of digital technology, particularly advanced tools. For example, while digital technology facilitates sharing of scientific knowledge, one year later, 60% to 80% of content published in 2016 was only available to readers via subscription or payment of a fee.

Digitalisation, science and science policy

Digitalisation is bringing change to all parts of science, from agenda setting, to experimentation, knowledge sharing and public engagement. Digital technology is facilitating a new paradigm of open science, a term referring to efforts to make scientific processes more open and inclusive. Open Science has three main pillars: open access (OA) to scientific publications and information; enhanced access to research data; and broader engagement with stakeholders. Together, the three pillars could increase the efficiency and effectiveness of science and speed the translation of research findings into innovation and socio-economic benefits. However, as described below, transitioning to open science requires the management of policy tensions associated with each pillar.

Accessing scientific information

Emerging OA publishing models and pre-print servers, mega-journals, institutional repositories and online information aggregators are simplifying access to scientific information. However, the new era brings challenges compared to traditional specialised journals that published scientific research after peer review. It is less clear how editorial and peer review processes will work and how the academic record will be maintained and updated over time.

Digital tools can support the publication of scientific papers in several ways. Information and communication technology (ICT) can help organise, share and analyse the growing volume of scientific information. At the same time, online open lab notebooks such as Jupyter provide access to primary experimental data and other information. Researchers are also employing AI to scrutinise suspicious scientific research and identify falsified data. Such tools depend on the broad adoption of standards and unique digital identifiers, which policy can facilitate.

Many science funders mandate OA publication, but academic careers, and in some cases institutional funding, are largely determined by publishing in high-impact, pay-for-access journals. Incentives and changes to evaluation systems need to match funders' mandates in order to transition faster to OA publication. A stronger focus on article-based metrics rather than journal impact factors is one way forward. New indicators and measures will also be required to incentivise data sharing.

Some fields of research are testing open post-publication peer review, whereby the wider scientific community can discuss a manuscript. Such a process has strengths and weaknesses, but with proper safeguards, post-publication peer review could bolster the quality and rigour of the scientific record.

Enhancing access to research data

Policies are needed to enhance access to research data. The OECD first advocated for greater access to data from publicly funded research in 2006. Since then, despite important progress, obstacles still limit access to scientific data:

- **The costs of data management are increasing, straining research budgets**. Science funders should treat data repositories as part of research infrastructure (which itself requires clear business models).
- **A lack of policy coherence and trust between communities hinders data sharing across borders**. The sharing of public research data requires common legal and ethical frameworks. Through such fora as the Research Data Alliance, funders should co-ordinate support for data infrastructure.
- **Science must adapt its governance and review mechanisms to account for changing privacy and ethical concerns**. Transparent, accountable, expert and suitably empowered governance mechanisms, such as research ethics committees, should oversee research conducted with new forms of personal data (in a world where new ICTs might also make personal data hard to anonymise).

- **Strategic planning and co-operation are required to build and provide access to cyber-infrastructure internationally**. Global bodies such as the aforementioned Research Data Alliance can help develop community standards, technical solutions and networks of experts.
- **The skills needed to gather, curate and analyse data are scarce**. New career structures and professions – such as "data stewards" – need to be developed for data management and analysis.

Broadening engagement with science

Digitalisation is opening science to a variety of societal actors, including patient groups, non-governmental organisations, industry, policy makers and others. Such opening aims to improve the quality and relevance of science and its translation into practice. Perhaps the most critical area of enlarged engagement is in setting priorities for research. If well designed, a more inclusive process of agenda setting could make research more relevant and might even generate entirely new research questions.

ICT is helping science elicit input from the networked public to label, generate and classify raw data, and draw links between data sets ("citizen science"). ICT is likewise creating opportunities for the networked public to take part in novel forms of collective discovery. Crowdfunding of science is also emerging. It appears to provide opportunities for small-scale but meaningful funding for young scholars with risky research projects.

Digital technology could benefit science by levering collective input in other ways. For example, recent research suggests that digital technology could help draw on the collective insight of the entire scientific community to improve allocation of public research funds (Box 1).

Artificial intelligence for science

AI might increase productivity in science at a time when – as discussed earlier – some evidence suggests research productivity may be falling (Bloom et al. 2017). AI is being used in all phases of the scientific process, from automated extraction of information in scientific literature, to experimentation (the pharmaceutical industry commonly uses automated high-throughput platforms for drug design), large-scale data collection, and optimised experimental design. Today, AI is regularly the subject of papers published in the most prestigious scientific journals.

As AI plays a greater role in science, certain policies will grow in importance. These include policies that affect access to high-performance computing (HPC) (the computational resources essential to some leading-edge fields of research, including in AI, can be extremely expensive), skills, and access to data (such as standardisation for machine readability of scientific datasets). Policies on access to data not only matter for training AI systems, and for the scope of scientific problems on which AI can operate, they also matter for reproducibility. Without access to underlying data, the validity of conclusions arrived at by complex algorithms – some of which may already have a "black box" character – will be open to question. AI in science also raises new and so far unanswered questions: for instance, Should machines be included in academic citations?

Box 1. Collective intelligence to help allocate science funding

Bollen et al. (2014) and Bollen (2018) examine a new class of Self-Organized Funding Allocation (SOFA) systems to address issues associated with peer review. Peer review is the dominant approach to assessing the scientific value of proposals for research funding. However, critique of peer review is mounting. A major concern is the opportunity cost of scientists' time. For example, one study in Australia found that 400 years of researchers' time was spent preparing unfunded grant proposals for support from a single health research fund (Herbert, Barnett and Graves, 2013).

To lower administrative overheads and improve funding allocation, Bollen and colleagues propose a SOFA system. Funding agencies would give all qualified scientists an unconditional and equal baseline amount of money each year. Scientists would then distribute a fixed percentage of their funding to peers who they think would make best use of the money. Every year, all scientists would therefore receive a fixed grant from their funding agency and an amount passed on by peers. Scientists could log on to their funding agency's website and simply select the names of scientists to whom they wish to donate, and indicate the amount for each. Individual distributions would be anonymous (to avoid personal influence) and subject to conflict of interest restrictions.

As funding circulates between scientists, it would come to reflect the funding preferences of the entire scientific community, not small review panels. At the same time, because all scientists receive an unconditional yearly grant, they would have greater stability and autonomy. Scientists would also have incentives to share research because if colleagues were positively impressed, more funding could follow. In addition, funding people rather than projects might provide scientists with more freedom to explore new research paths.

Using millions of Web of Science records, simulation of a SOFA yielded a distribution of funding similar to that produced by grant review, but without a single proposal being prepared (Bollen et al., 2014). SOFAs merit further study and pilot testing.

Digitalisation and innovation in firms

Digitalisation is also shaping innovation throughout the economy, generating new digital products and services and enhancing traditional ones with digital features. Four trends characterise innovation in the digital age:

- **Innovation processes increasingly rely on data.** They use data to explore product and services development, and gain insight on market trends; to understand the behaviour of competitors; to optimise development, production and distribution processes; and to tailor products and services to specific or fluctuating demand. More diverse, real-time and voluminous types of data have driven the development of new business models, such as on-demand mobility services (e.g. Uber) and platforms to search, compare and book accommodation and transportation options (e.g. Booking.com).

- **Digital technologies facilitate services innovation.** Examples include new digitally enabled services, such as predictive maintenance services using the Internet of Things and web-based business services.

- **Digital technology speeds innovation.** Digital innovations such as generative design software and three-dimensional (3D) printing speed innovation cycles by accelerating product design, prototyping and testing. ICTs also enable the market launch of product beta versions that can be updated to incorporate consumer feedback. For example, GE Appliances' FastWorks system involves consumers early in the development of new products such as refrigerators.

- **Digital technology makes innovation ecosystems more open and diverse.** Digital technology lowers the costs of communication, regardless of location, spurring interaction. Firms interact with research institutions and other firms to gain access and exposure to complementary expertise and skills, and to help share the costs and risks of uncertain investments in digital innovation. One example of a collaboration using digital technology is the SmartDeviceLink Consortium, an open-source platform for smartphone app development for vehicles created by Ford and Toyota.

Does innovation policy need to be adapted for the digital age?

Innovation policies need to align with generic features of digital technology, and: ensure access to data for innovation; provide suitably designed support and incentives for innovation and entrepreneurship; design innovation ecosystems that support competition; and, support collaboration for innovation. Table 1 summarises where innovation policies may need to be re-designed around specific features of digital technology.

Table 1. Major changes to innovation policies called for by digitalisation, by policy domain

Policy domain	Changes required
Access to data	• Ensure access to data for innovators, taking into account the diversity of data and preserving rights and incentives[1] • Explore the development of markets for data
Business innovation and entrepreneurship	• Ensure that policies are anticipatory, responsive and agile • Support service innovation that implements digital technologies • Adapt the intellectual property (IP) system • Support the development of generic (multi-purpose) digital technologies[1]
Public research, education and training	• Promote open science (access to data, publications) • Support training in digital skills for science • Support interdisciplinarity in research • Invest in digital infrastructure for science • Facilitate co-creation between industry, science and civil society • Ensure that skills needed for digital innovation are being developed (in collaboration with education and labour market policy authorities) • Support education and training for the development of managerial skills
Competition, collaboration and inclusiveness	• Review competition policies from the perspective of innovation in the digital age (e.g. rules regarding takeovers and standards; IP systems) • Support digital technology adoption by all firms, particularly SMEs[1] • Support social and territorial inclusiveness in digital innovation activities
Cross-cutting principles	• Engage with citizens to address technology-related public concerns • Adopt a sectoral approach to policy making when necessary

1. These areas require a sectoral approach to innovation policy making.
Note: SMEs = small and medium-sized enterprises.

Digitalisation and the next production revolution

Digital technologies are at the heart of advanced production. The widely used term "Industry 4.0" refers to a new paradigm in which all stages of manufacturing – from product design to industrial research – are controlled and/or connected by digital technology. Industry 4.0 technologies can raise productivity in many ways, from reducing machine downtime when intelligent systems predict maintenance needs, to performing work faster, more precisely and consistently with increasingly autonomous, interactive and inexpensive robots. The digital production technologies in question are evolving rapidly. For instance, recent innovations permit 3D printing with novel materials such as glass, printing strands of DNA, and even, most recently, printing on gels using light (OECD, 2017; Castelvecchi, 2019).

AI in production

With the advent of deep learning using artificial neural networks – the main source of recent progress in AI – AI is finding applications in most industrial activities. Such uses range from optimising multi-machine systems to enhancing industrial research. For example, AI is exploring decades of experimental data to radically shorten the time needed to discover new industrial materials, sometimes from years to days. Beyond production, AI is also supporting functions such as logistics, data and information retrieval, and expense management.

Without large volumes of training data, many AI/machine learning (ML) models are inaccurate. But many industrial companies do not have the in-house capabilities to exploit the value in their data, and are understandably reluctant to let others access their data. Some public programmes exist to bridge between company data and external analytic expertise. In addition, to help develop and share training data, governments can work with stakeholders to develop voluntary model agreements and programmes for trusted data sharing. More generally, governments can promote open-data initiatives and data trusts, and ensure that public data exist in machine-readable formats. While such actions are not usually aimed at industry, they can be helpful to industrial firms in incidental ways (for instance in research, or in demand forecasting that draws on economic data, etc.).

In addition, while AI entrepreneurs might have the knowledge and financial resources to develop a proof-of-concept for a business, they sometimes lack the hardware and hardware expertise to build an AI company. Governments can help resolve such constraints.

Developing digital skills

Digitalisation raises demand for digital skills. Occupations like "industrial data scientist" and "bioinformatics scientists" are recent, reflecting a rate of technological change that is generating skills shortages. A dearth of data specialists is impeding the use of data analytics in business. Some countries also have too few teachers of computer programming (Stoet, 2016). A shortage of cybersecurity experts has led at least one university to recruit students to protect itself against hackers (Winick, 2018). Furthermore, the general-purpose nature of digital technology means that skills required to be a good scientist are also increasingly attractive in industry, adding to competition for talent (Somers, 2018).

Education and training systems must draw on information from all social partners

Skills forecasting is prone to error. Because foresight is inherently uncertain, education and training systems should draw on information about skills needs from businesses, trade unions, educational institutions and learners. Students, parents and employers also need access to data with which to judge the performance of educational institutions. In turn, resources in educational and training systems must flow efficiently to courses and institutions that best match skills demand. Institutions that play such roles include Sweden's job security councils and SkillsFutureSingapore.

New courses and curricula may be needed

New courses and curricula may be needed to keep pace with rapid changes brought on by digitalisation. Advances in digital technology may require entirely new fields of tuition, such as dedicated programmes for the autonomous vehicle industry. Existing curricula may also need to change. For example, software engineers are effectively becoming social engineers. Society might benefit if they were to learn civics and philosophy, subjects rarely taught in science, technology, engineering and mathematics programmes (Susskind, 2018). Greater multidisciplinary education is often necessary. For instance, the bioeconomy increasingly requires degree programmes that combine biology, engineering and programming.

Many countries have far-reaching programmes to develop digital technology skills. Using online tuition, Finland aims to teach every citizen the basics of AI. All Finnish students in initial education learn coding. Furthermore, digital technology is creating novel ways to deliver skills (Box 2).

> **Box 2. Using digital technology to deliver skills**
>
> Digital technologies are beginning to facilitate skills development in new ways. In 2014, for example, Professor Ashok Joel and graduate students at Georgia Tech University created an AI teaching assistant – Jill Watson – to respond to online student questions. For months, students were unaware that the responses were non-human. iTalk2Learn, a European Union project, aims to develop an open-source intelligent platform for mathematics tutoring in primary schools. In France, on an experimental basis, haptic technology – which allows a remote sense of touch – has shortened the time required to train surgeons, and promises many other applications.
>
> Augmented reality (AR) uses computer vision to overlay objects in the user's field of view with data and annotations (such as service manual instructions). Tesla has applied for a patent for an "Augmented Reality Application for Manufacturing", built into safety glasses. With AR, skills such as those needed to repair breakdowns in complex machine environments will effectively become downloadable.
>
> Virtual reality (VR) environments could improve the speed and retention of learning, as is beginning in industry. Using VR, Bell Helicopter reports reducing a typical six-year aircraft design process to six months. VR could also permit safe low-cost learning in fields where this is otherwise too dangerous or expensive.
>
> The declining cost of VR and AR, and the integration of AR into mobile devices, should lower barriers to public participation in education, training and research. Elon Musk, for example, promises a high-definition VR live-stream of a future SpaceX moon mission (Craig, 2018).

Facilitating the diffusion of digital technologies and tools

Most countries, regions and companies are primarily technology users, rather than technology producers. For them, technology diffusion and adoption should be priorities. Technology diffusion helps raise labour productivity growth and may also lower inequality in wage growth rates. Policy makers tend to acknowledge the importance of technology diffusion, but to underemphasise it in the overall allocation of resources.

Even in the most advanced economies, diffusion of technology can be slow or partial. One recent study examined 60 manufacturers in the United States with annual turnovers of between USD 500 million and USD 10 billion. The study found that just 5% had mapped where AI opportunities lie within their company and were developing a strategy for sourcing the data AI requires, while 56% had no plans to do so (Atkinson and Ezell, 2019).

New digital technologies may make diffusion more difficult

Certain features of new digital technologies could hinder diffusion. As technology becomes more complex, potential users must often sift through burgeoning amounts of information on rapidly changing technologies and knowledge requirements. Once the technology is chosen, deployment can pose difficulties as well. For instance, a typical industrial plant might contain machinery of many vintages from different manufacturers. This machinery may have control and automation systems from different vendors, all operating with different communication standards. To deploy AI, firms must often invest in costly information technology upgrades to merge data from disparate record-keeping systems (consumer and supply-chain transactions are often separate, for instance). Firms also have unique challenges – from proprietary data types to specific compliance requirements. These conditions may require further research and customisation (Agrafioti, 2018). Difficulties in determining the rate of return on some AI investments may also hinder adoption.

Institutions for diffusion can be effective, if well designed

Various micro-economic and institutional settings facilitate diffusion. These range from supportive conditions for new-firm entry and growth, to economic and regulatory frameworks for efficient resource allocation. In addition to enabling framework conditions, effective institutions for technology diffusion also matter. Institutions for diffusion range from applied technology centres such as the Fraunhofer Institutes in Germany to open technology mechanisms such as the Bio-Bricks Registry of Standard Biological Parts.

New diffusion initiatives are emerging, often involving partnership-based approaches. An example is the US National Network for Manufacturing Innovation (NNMI). The NNMI uses private non-profit organisations as the hub of a network of company and university organisations to develop standards and prototypes in areas such as 3D printing and digital manufacturing. Some initiatives aim to facilitate the testing of new digital technology applications, such as by creating test beds, regulatory sandboxes, and state-of-the-art facilities as well as providing expertise.

To strengthen the interface between science and industry, governments should also support platform technologies. These could include biofoundries, distributed R&D networks, data curation and digital/genetic data storage. This is a public role because the associated investment risks are too high for the private sector. Moreover, for the private sector such investments may not provide a clear route to market.

Technology diffusion institutions need realistic goals and time horizons

Effective diffusion is more likely under two conditions. First, technology diffusion institutions must be empowered and resourced to take longer-term perspectives. Second, evaluation metrics must emphasise longer-run capability development rather than incremental outcomes and revenue generation (Shapira and Youtie, 2017). Diffusion in SMEs involves particular challenges, which reflects, among other reasons, the more limited availability of digital skills in SMEs (Box 3).

Box 3. Diffusing digital technology to SME: Some key considerations

Various measures can help diffuse digital technology to SMEs, including:

- Systematising key information for SMEs. For example, Germany's Industry 4.0 initiative has documented over 300 uses cases of applications of digital industrial technologies, along with contacts to experts (www.plattform-i40.de).
- Providing information on the expected return on investments in new technologies, as well as information on essential complementary organisational and process changes.
- Providing signposts to reliable sources of SME-specific expertise, because the skills to absorb information are scarce in many SMEs. For example, Tooling U-SME, an American non-profit organisation owned by the Society of Manufacturing Engineers, provides online industrial manufacturing training and apprenticeship programmes.
- Providing facilities where SMEs can test varieties and novel combinations of equipment to help de-risk prospective investments.

Committing to public sector research

The technologies discussed in this publication have arisen because of advances in scientific knowledge and instrumentation. Publicly financed basic research has often been critical. For decades, for example, public funding supported progress in AI, including during periods of unproductive research. Today, AI attracts huge private investment. In this context, a recent hiatus – and in certain cases decline – in government support for research in some major economies is a concern (Figure 2).

Figure 2. Trends in total R&D performance, OECD countries and selected economies, 1995-2015

As a percentage of GDP
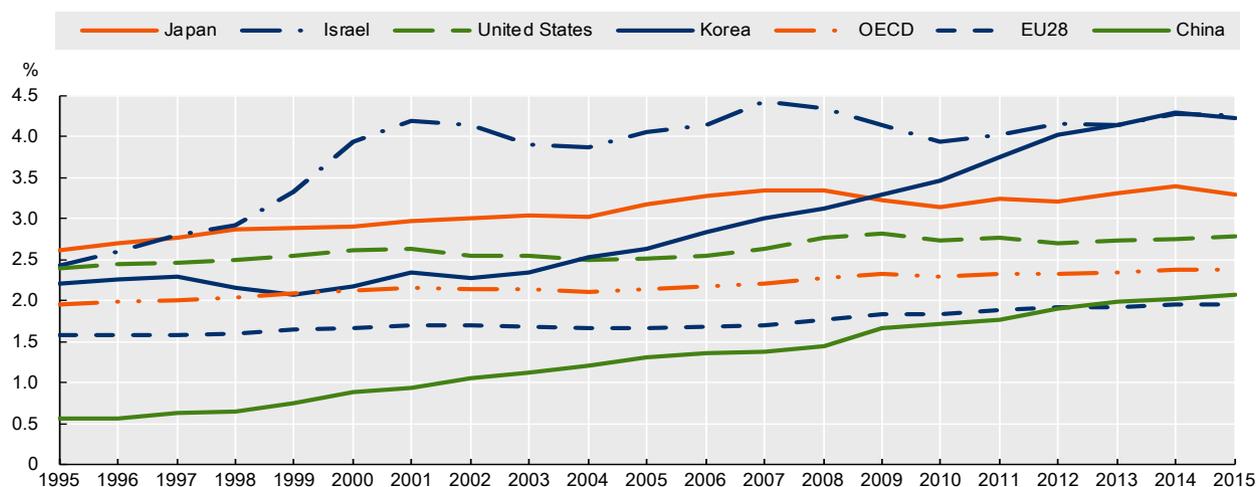
Note: R&D = research and development; GDP = gross domestic product.
Source: OECD (2017), *OECD Science, Technology and Industry Scoreboard 2017: The Digital Transformation*, http://dx.doi.org/10.1787/9789264268821-en.

StatLink 🖷🖵🛤 https://doi.org/10.1787/888934075678

Multidisciplinary research

The importance of understanding the interplay between disciplines reflects the need to address complex and cross-cutting problems, the fact that new disciplines are born as knowledge expands, convergence among technologies, and the increased complexity of scientific equipment.

Policies on hiring, promotion and tenure, and funding systems that privilege traditional disciplines, may impede interdisciplinary research. Scientists need to know that working at the interface between disciplines will not jeopardise opportunities for tenure. Institutions that demonstrably support multidisciplinary research can provide useful lessons.

Public-private research partnerships

The complexity of some emerging digitally based technologies exceeds the research capacities of even the largest individual firms. This necessitates a spectrum of public-private research partnerships. For example, materials science relies on computational modelling, enormous databases of materials' properties and expensive research tools. It is almost impossible to gather an all-encompassing materials science R&D infrastructure in any single company or institute.

Many possible targets exist for government R&D and commercialisation efforts to continue progress in the digital revolution. These range from quantum computing, to creating more robust forms of AI.

Developing technology- and sector-specific capabilities in government

Without governments fully understanding technologies and sectors, strategic opportunities to benefit from digital technologies might be lost – especially when technology is evolving quickly.

Regulation, when used, also needs deep technology and industry-specific understanding. The effects of regulation on innovation can be complex, of uncertain duration and ambiguous, making them difficult to

predict. Developments in fast-changing technologies such as AI may also require that regulatory processes become more anticipatory and innovative.

Technical expertise in government will help avoid unrealistic expectations about new technologies, especially those emerging from science (such as quantum computing). New discoveries and technologies often attract hyperbole. No more than six years ago, for example, massive open online courses (MOOCs) were widely held to represent a democratising transformation in postsecondary education. However, recent research shows that less than 12% of MOOC students return for a second year, and most students come from affluent families in rich countries (Reich and Ruipérez-Valiente, 2019).

Effective sectoral support requires, as a first step, mechanisms to strengthen policy intelligence. These mechanisms include roadmaps or sectoral plans prepared with industry and social partners. One example is the Sector Competitiveness Plans developed by Industry Growth Centres in Australia. Developing a shared vision for the future, with industry and social partners, is also useful.

Ensuring access to complementary infrastructures

Certain types of infrastructure help to utilise digital technology. These include HPC, cloud computing and fibre-optic connectivity. HPC is increasingly important for firms in industries ranging from construction and pharmaceuticals to the automotive sector and aerospace. However, like other digital technologies, manufacturing's use of HPC falls short of potential. A number of possible ways forward exist. SMEs could receive low-cost, or free, limited experimental use of HPC, while online software libraries/clearing houses could help disseminate innovative HPC software to a wider industrial base.

Industry 4.0 requires increased cloud-based data sharing, analysis, monitoring and control within and across production sites and company boundaries. The cloud will also allow independent AI projects to start small, and scale up or down as required. Indeed, Google's chief AI scientist, Fei-Fei Li, argues that cloud computing will democratise AI. Cloud computing will also increasingly help data sharing and analysis in science: Amazon Web Services, for instance, participates in the 1 000 Genomes Project, helping researchers to access and analyse vast amounts of cloud-based genetic data. However, cloud use varies greatly between small and large firms, and across countries. Broadband networks – especially fibre-optic connectivity – are also essential to Industry 4.0.

Optimising digital systems to strengthen science and innovation policies

Digital science and innovation policy (DSIP) systems use digital procedures and infrastructures to help formulate and deliver science and innovation policy. They are used to monitor policy interventions, develop new STI indicators, assess funding gaps, strengthen technology foresight, and identify leading experts and organisations. Data are mainly sourced from funding agencies (e.g. databases of grant awards), R&D-performing organisations, proprietary bibliometric and patent databases, and the web.

There are various types of DSIP system. Databases of public funders are one type, of which Belgium's Flanders Research Information Space is an example. A second type of DSIP infrastructure is a Current Research Information System. Through the Estonian Research Information System (ETIS), for example, Estonian higher education institutions (HEIs) manage research information and showcase research. Public funders use ETIS to evaluate and process grant applications. National research assessments and evaluations also draw on ETIS.

A third type of DSIP infrastructure is what might be termed an "intelligent system". For example, to examine the socio-economic impacts of research, Japan's SciREX Policymaking Intelligent Assistance System uses big data and semantic technologies (which aim to extract meaning from data). They help to process data on Japan's research outputs and impacts, funding, R&D-performing organisations and research projects.

Ensuring interoperability in DSIP systems

DSIP systems pull data from multiple sources, linking them to gain policy insights that are otherwise impossible to achieve. But linking data is problematic, chiefly on account of different data standards. Recent years have seen attempts to establish international standards and vocabularies to improve data sharing and interoperability in science and research management. Many DSIP infrastructures have adopted such standards to link data from universities, funding bodies and publication databases, thereby relating research inputs to research outputs.

Using DSIP systems in research assessment

Many metrics aim to quantify scientific quality, impact and prestige. More than half of the DSIP systems identified in OECD work play a role in research assessment. The growing digital footprint of academic and research activities suggests that, in future, most relevant dimensions of research activity might be represented digitally (including metrics generated from social media).

The roles of the business sector in DSIP

Non-government actors are emerging as a main force in DSIP systems. For example, multinational corporations like Alphabet Inc. and Microsoft Inc., and national technology companies such as Baidu Inc. (China) and Naver Inc. (Korea), have designed platforms to search academic outputs. In the future, these platforms could become key parts of national DSIP systems.

Harnessing private sector developments in public DSIP systems has many potential benefits. Solutions can be implemented quickly and at an agreed cost. Private companies can promote interoperability through their standards and products. However, outsourcing to the private sector may bring risks. These could include loss of control over the development of DSIP systems, discriminatory access to data and even the emergence of private platforms that become dominant because of hard-to-contest network effects.

The outlook for DSIP systems

Governments need to shape DSIP ecosystems to fit their needs. This will require interagency co-ordination, sharing of resources (such as standard digital identifiers) and coherent policy frameworks for data sharing and reuse in the public sector. Since several government ministries and agencies formulate science and innovation policy, DSIP systems should involve co-design, co-creation and co-governance. In a desirable future, DSIP infrastructures will provide multiple actors in STI with up-to-date linked microdata. Policy frameworks will have resolved privacy and security concerns, and national and international co-operation on metadata standards will have addressed interoperability issues.

Digitalisation in science and innovation: Possible "dark sides"

Digitalisation offers many positive opportunities for STI, so long as complementary policies receive proper attention. But possible unwelcome outcomes from digitalisation in STI also exist. These include widening capability gaps across countries and subnational regions, negative effects on science processes, excessive complexity in machine ecosystems, and risks that are diffuse, hard to foresee and primarily social. Two areas of possible concern – described below - relate to complex systems, and negative impacts on science from digitalisation. Evidence on the likelihood or scale of these undesirable outcomes is scant. Greater awareness and further study are necessary.

Policy makers can mitigate technological risk in several ways. They can earmark part of research budgets to study the broader implications of science. Engaging the public in debate, while avoiding hyperbole about technology, is useful. In addition, they can ensure that science advice is trustworthy. Investments in research and innovations that reduce risk (such as in cyber-security) might also help.

Complex systems and unmanageable machine ecologies

Governments need improved understanding of complex systems (Nesse, 2014). As a wide array of critical systems becomes more complex, mediated and interlinked by code, the risk and consequences of vulnerabilities could increase. As code controls a growing number of connected systems, errors can cascade, with effects that become more extensive than in the past. For instance, owing to software faults, the United States recently experienced the first national – rather than local – 911 outages (Somers, 2017). The ability to anticipate failures in complex critical systems could also diminish (Arbesman, 2016).

AI and other measures will help to automate and improve software verification. Nevertheless, as the physicist Max Tegmark observes "the very task of verification will get more difficult as software moves into robots and new environments, and as traditional pre-programmed software gets replaced by AI systems that keep learning, thereby changing their behaviour…" (Tegmark, 2017).

An inbuilt feature of technology is that it deepens complexity: systems accumulate parts over time, and more connections develop between those parts. Technologies that become more complex can end up depending on antiquated legacy systems. This is especially so for code. For example, in the lead up to 1 January 2000, amid Y2K concerns, the US Federal Aviation Administration examined computers used for air traffic control. One type of machine required fixing, an IBM 3083 that had been installed in the 1980s. However, only two persons at IBM knew the machine's software, and both had retired (Arbesman, 2016).

Negative impacts on science from digitalisation

OECD research indicates that a sizeable number of scientists think digitalisation will have at least some negative effects on science. These include the growth of hypothesis-free research in data-driven science, and divides in research between those who possess advanced digital competences and those who don't. Digitalisation could also encourage a celebrity culture in science, lead to premature diffusion of research findings and expose individuals to pressure groups. Other concerns are the use of readily available but inappropriate indicators for monitoring and incentivising research, and the potential concentration of workflows and data in the hands of a few companies providing digital tools.

Another potentially problematic issue is the misapplication of AI in science and society. The design and use of effective AI systems requires expertise which is scarce. Moreover, stricter requirements on performance, robustness, predictability and safety will increase the need for expertise. AI systems built on deep learning techniques often suffer from deficiencies in performance, robustness, predictability and safety, outcomes that even AI experts can struggle to achieve (Hoos, 2018). Hoos and others propose building a next generation of AI systems known as Automated AI, to help develop and deploy accurate and reliable AI without the need for deep and highly specialised AI expertise. Automated AI builds on work on automated algorithm design, and automated ML, which is developing rapidly in academia and industry.

The untapped potential of digital technology for STI policy

Innovations in digital technology will prompt new ideas for how digital technology might support policy for science and innovation. Examples considered here are prediction markets, various applications of blockchain, and using social media to increase exposure to innovation in a selective way. Some of these ideas have yet to receive significant attention, and few governments have experimented with the opportunities available.

Prediction markets for STI policy

Prediction markets, which involve trading bets on whether some specific outcome will occur, could inform STI policy. Prediction markets have outperformed the judgement of experts in forecasting outcomes in fields as diverse as sporting tournaments and political elections. Prediction markets incentivise participants to

find or generate new information (from which profit could derive). Recent experiments show that prediction markets might accomplish the following:

- Predict the results of otherwise expensive research evaluations (e.g. of HEIs).
- Quickly and inexpensively identify research findings that are unlikely to replicate.
- Help optimally allocate limited resources for replications.
- Help institutions assess whether strategic actions to improve research quality are achieving their goals.
- Test scientific hypotheses.
- Help understand specific scientific processes.

Specialised digital platforms make it easier to implement prediction markets. On the Augur platform, for example, with an initial commitment of less than a dollar, anyone can ask a question and create a market based on a predicted outcome. Using prediction markets in STI appears more constrained by tradition than by technical infeasibility.

Blockchain for science, technology and innovation

One leading commentator has described blockchain as follows: "blockchain technology facilitates peer-to-peer transactions without any intermediary such as a bank or governing body…the blockchain validates and keeps a permanent public record of all transactions. This means that personal information is private and secure, while all activity is transparent and incorruptible – reconciled by mass collaboration and stored in code on a digital ledger" (Tapscott, 2015). Technical and policy challenges such as interoperability must be resolved before blockchain in STI can be widely deployed. But proposals to use blockchain in STI are flourishing (Box 4).

Box 4. Possible applications of blockchain in science and innovation

Recent proposals for how blockchain might benefit STI include the following:

- **Establishing a cryptocurrency for science**. Using a cryptocurrency, publishers of scientific works could receive micro-payments as content is consumed. A science cryptocurrency could also facilitate a system of rewards for sometimes under-rewarded activities such as statistical support, exchange of lab equipment, data hosting and curation, and peer review (van Rossum, 2018).

- **Storing and sharing research data**. Databases that encompass large parts of the research ecosystem are technically possible. However, the need for centralised management and ownership complicates their implementation. Data security and ease of access are just some of the concerns. In principle, the blockchain could make scalable, safe and decentralised data stores more practical. It could also enhance the reproducibility of science by automatically tracking and recording work such as statistical analysis, while reducing the risk of data fraud (van Rossum, 2018).

- **Making ownership of creative material transparent**. Commercial services now offer secure attribution of ownership of creative works by providing a blockchain-verified cryptographic ID (Stankovic, 2018). Launched in 2018, Artifacts is a platform for publishing any material that researchers consider worth sharing. This ranges from data sets to single observations, hypotheses and negative research results, all logged to the blockchain. Artifacts aims to disseminate more scientific information, securely and in citable ways, more quickly than occurs with peer-reviewed written articles (Heaven, 2019).

- **Broadening access to supercomputing**. Golem aims to create a global supercomputer, accessible to anyone, using processing power from idle computers and data centres around the world. Users would rent processing time from each other, and rely on blockchain to track computations and payments, and to keep data secure (Golem, n.d.).

Using social media to spread innovation

People's propensity to innovate involves an element of imitation. Research shows that children who grow up in areas with more inventors are more likely to become inventors. Greater exposure to innovation among minorities and children from low-income families might increase the prevalence of innovation. Among other measures, social media could provide a channel for targeted interventions (Bell et al., 2019).

Conclusion

Scientific progress cannot be taken for granted. There are many areas of science – fundamental to human well-being – where knowledge is still surprisingly limited. For example, the process by which *E. coli* (a bacterium) consumes sugar for energy is one of the most basic biological functions, and also important for industry. But how the process operates has not been fully established, even though research on the subject was first published over 70 years ago. Uncertainty also exists on many critical questions in climate science. To cite two, what is the tipping point for the inversion of the flows of cold and hot oceanic waters? When could changes become irreversible (e.g. melting of West Antarctic or Greenland ice-shelves)?

Progress in STI is also necessary because, despite striking advances in technology, the pace of innovation is insufficient in some crucial fields. For instance, today's leading energy generation technologies were mostly developed or demonstrated over a century ago. The combustion turbine was invented in 1791, the fuel cell in 1842, the hydro-electric turbine in 1878 and the solar photo-voltaic cell in 1883. Even the first nuclear power plant began operating over 60 years ago. The performance of all these technologies has, of course, improved. But truly disruptive breakthroughs have not occurred (Webber, Duncan and Gonzalez, 2013). Indeed, some high-profile commentators from academia and industry have gone further, claiming (debatably) that a more general innovation plateau has been reached.

Furthermore, efficient and effective policies for STI are ever more important in countries where rapid population ageing is likely to constrain discretionary public spending over the long run. For these and other reasons, utilising the full potential of digital technology in STI is important.

References

Agrafioti, F. (2018), "How to set up an AI R&D lab", *Harvard Business Review,* 20 November, https://hbr.org/2018/11/how-to-set-up-an-ai-rd-lab.

Arbesman, S. (2016), *Overcomplicated: Technology at the Limits of Comprehension*, Penguin Random House, New York.

Atkinson, R.D. and S. Ezell (2019), "The Manufacturing Evolution: How AI will Transform Manufacturing and the Workforce of the Future", Information Technology and Innovation Foundation, Washington DC, https://itif.org/publications/2019/08/06/manufacturing-evolution-how-ai-will-transform-manufacturing-and-workforce.

Bell, A.M. et al. (2019), "Who becomes an inventor in America? The importance of exposure to innovation", *NBER Working Paper* No. 24062, issued in November 2017, revised in January 2019, National Bureau of Economic Research, Cambridge, Massachusetts, www.nber.org/papers/w24062.

Biles, S. (28 December 2018), "Tiny computers could transform our lives", Scientific American Observations blog, https://blogs.scientificamerican.com/observations/tiny-computers-could-transform-our-lives/.

Bloom, N. et al. (2017), "Are ideas getting harder to find?", *NBER Working Paper* No. 23782, September, National Bureau of Economic Research, Cambridge, Massachusetts, https://www.nber.org/papers/w23782.

Bollen, J. (2018), "Who would you share your funding with?", *Nature*, Vol. 560, Nature Research, Springer,p.143, www.nature.com/articles/d41586-018-05887-3.

Bollen, J. et al. (2014), "From funding agencies to scientific agency: Collective allocation of science funding as an alternative to peer review", *EMBO Reports*, Vol. 15/1, Wiley Online Library, pp. 131-133, https://onlinelibrary.wiley.com/doi/full/10.1002/embr.201338068.

Castelvecchi, D. (2019), "Forget everything you know about 3-D printing – the 'replicator' is here", *Nature,* Vol. 566, Nature Research, Springer, p. 17, http://doi.org/10.1038/d41586-018-07798-9.

Corea, F. (2017), "The convergence of AI and blockchain: What's the deal?", *Medium,* 1 December, https://medium.com/@Francesco_AI/the-convergence-of-ai-and-blockchain-whats-the-deal-60c618e3accc.

Craig, E. (2018), "An overview of the possibilities and challenges in delivering STEM education using AR and VR", presentation at the workshop on digital technology for science and innovation, Oslo, 5-6 November, www.oecd.org/sti/inno/digital-technology-for-science-and-innovation-emerging-topics.htm.

Evans, B. (2019), "5G: If you build it, we will fit it", benevans.com, 16 January, www.ben-evans.com/benedictevans/2019/1/16/5g-if-you-build-it-we-will-fill-it.

Golem (n.d.), Golem website, https://golem.network/ (accessed 20 June 2019).

Heaven, D. (2019), "Bitcoin for the biological literature", Nature, Vol. 566, Nature Research, Springer, pp. 141-142, www.nature.com/articles/d41586-019-00447-9.

Herbert, D.L, A.G. Barnett and N. Graves (2013), "Australia's grant system wastes time", *Nature*, Vol. 495, 21 March, Nature Research, Springer, pp. 314, www.nature.com/articles/495314d.

Hoos, H.H. (2018), "Democratisation of AI by automating the creation of AI systems", presentation at digital technology for science and innovation workshop, Oslo, 5-6 November.

Hutson, M. (2017), "The future of AI depends on a huge workforce of human teachers", *Bloomberg Businessweek*, 7 September, www.bloomberg.com/news/articles/2017-09-07/the-future-of-ai-depends-on-a-huge-workforce-of-human-teachers.

Kelly, K. (2013), "The post-productive economy", The Technium, https://kk.org/thetechnium/the-post-produc/.

Metz, C. (2019), "'Businesses will not be able to hide': Spy satellites will give edge from above", 24 January, *The New York Times*, https://www.nytimes.com/2019/01/24/technology/satellites-artificial-

intelligence.html.

Nesse, R. (2014), "The Fragility of Complex Systems", in Brockman, J. (ed.), *What Should We Be Worried About?*, Harper Perrenial, New York, London, Toronto, Sydney, New Delhi, Auckland.

OECD (2019a), *Going Digital: Shaping Policies, Improving Lives,* OECD Publishing, Paris, https://doi.org/10.1787/9789264312012-en.

OECD (2019b), *Measuring the Digital Transformation: A Roadmap for the Future,* OECD Publishing, Paris, https://doi.org/10.1787/9789264311992-en

OECD (2017), *OECD Science, Technology and Industry Scoreboard 2017: The Digital Transformation*, OECD Publishing, Paris, http://dx.doi.org/10.1787/9789264268821-en.

OECD (2015), "Daejeon Declaration on Science, Technology, and Innovation Policies for the Global and Digital Age", webpage, www.oecd.org/sti/daejeon-declaration-2015.htm (accessed 20 June 2019).

Reich, J. and J.A. Ruipérez-Valiente (2019), "The MOOC Pivot: What happened to disruptive transformation of education?", *Science,* 11 January, Vol. 363/6423, American Association for the Advancement of Science, Washington, DC, pp. 130-131, https://science.sciencemag.org/content/363/6423/130.summary.

Shapira, P. and J. Youtie (2017), "The next production revolution and institutions for technology diffusion", in *The Next Production Revolution: Implications for Governments and Business*, OECD Publishing, Paris, https://doi.org/10.1787/9789264271036-11-en.

Somers, J. (2018), "The scientific paper is obsolete: Here's what's next", *The Atlantic*, 5 April, www.theatlantic.com/science/archive/2018/04/the-scientific-paper-is-obsolete/556676/.

Somers, J. (2017), "The coming software apocalypse", *The Atlantic*, 26 September, www.theatlantic.com/technology/archive/2017/09/saving-the-world-from-code/540393/.

Stankovic, M. (2018), "Using blockchain to facilitate innovation in the creative economy", presentation at the digital technology for science and innovation workshop, Oslo, 5-6 November.

Stoet, G. (2016), "Maths anxiety is creating a shortage of young scientists … here's a solution", The Conversation, 1 June, http://theconversation.com/maths-anxiety-is-creating-a-shortage-of-young-scientists-heres-a-solution-58889.

Susskind, J. (2018), *Future Politics,* Oxford University Press, United Kingdom.

Tapscott, D. (2015), "Blockchain revolution: How the technology behind Bitcoin is changing money, business and the world", Don Tapscott, http://dontapscott.com/2015/06/blockchain-revolution-the-brilliant-technology-changing-money-business-and-the-world/ (accessed 20 June 2019).

Tegmark, M. (2017), Life 3.0: Being Human in the Age of Artificial Intelligence, First Vintage Books, New York.

van Rossum, J. (2018), "The blockchain and its potential for science and academic publishing", presentation at the digital technology for science and innovation workshop, Oslo, 5-6 November.

Webber, M.E., R.D. Duncan and M.S. Gonzalez (2013), "Four technologies and a conundrum: The glacial pace of energy innovation", *Issues in Science and Technology,* Vol. xxix/2, Winter, National Academy of Sciences, National Academy of Engineering, Institute of Medicine, University of Texas at Dallas, www.issues.org/29.2/Webber.html.

Winick, E. (2018), "A cyber-skills shortage means students are being recruited to fight off hackers", *MIT Technology Review*, 18 October, Massachusetts Institute of Technology, Cambridge, www.technologyreview.com/s/612309/a-cyber-skills-shortage-means-students-are-being-recruited-to-fight-off-hackers/?source=download-metered-content.

Youn, H. et al. (2015), "Invention as a combinatorial process: Evidence from US patents", *Journal of the Royal Society Interface*, 6 May, Royal Society, London, https://doi.org/10.1098/rsif.2015.0272. Governments can promote open data initiatives

The Digitalisation of Science, Technology and Innovation

KEY DEVELOPMENTS AND POLICIES

This report examines digitalisation's effects on science, technology and innovation and the associated consequences for policy. In varied and far-reaching ways, digital technologies are changing how scientists work, collaborate and publish. While examining these developments, this book also assesses the effects of digitalisation on longstanding policy themes, from access to publicly funded research data, to the diffusion of technology and its absorption by firms. New and emerging topics are also explored. These include the roles of artificial intelligence and blockchain in science and production, using digital technology to draw on the collective intelligence of the scientific community, advances in the digitalisation of biotechnology, and possible «dark sides» of digitalisation.