The Alan Turing Institute

Building resilience in government using data science

Successes and recommendations from The Alan Turing Institute's AI for science and government programme

The Alan Turing Institute

About The Alan Turing Institute

The Alan Turing Institute is the national institute for data science and artificial intelligence (AI). Established in 2015, we are named in honour of Alan Turing, whose pioneering work in theoretical and applied mathematics, engineering and computing laid the foundations for the modern-day fields of data science and AI. Headquartered at the British Library in London, we partner with organisations across government, industry, academia and the third sector to undertake world-class research and innovation that benefits society.

About the ASG programme

Established in 2018, the AI for science and government (ASG) programme is a five-year, £38.8 million research programme at The Alan Turing Institute that aims to deploy AI and data science to address significant societal challenges. Funded through UK Research and Innovation's (UKRI's) Strategic Priorities Fund, and delivered in partnership with the Engineering and Physical Sciences Research Council (EPSRC), the programme brings together researchers from diverse disciplines to tackle problems including climate change, health emergencies, economic instability, and online harms.

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Executive summary

In the aftermath of crises, from world wars to global pandemics, governments often seek resilience in their rebuilding efforts. Prioritising resilience as an organisational value entails developing decision-making processes that are stable and adaptable.

Technology can help, but in recent decades governments have tended to use technology to pursue other objectives, such as economic efficiency. Modern data-intensive technologies, such as data science and artificial intelligence (AI), hold tremendous potential to rebuild resilience in government. However, changes are needed in order to realise this potential.

Researchers from the AI for science and government (ASG) programme at The Alan Turing Institute have been addressing these challenges under the multidisciplinary theme of ‘Shocks and resilience’ (S&R). In this white paper, we argue that developing resilience requires a new and distinctly public sector approach to data science, in which data-intensive technologies do not just automate or replicate what humans can already do well, but rather do things which people cannot – such as tackling difficult, multi-sector problems that have no ‘right’ solution. We illustrate our argument with selected case studies based on projects involving ASG researchers.

Based on our experiences under the S&R theme and within the broader ASG programme, we propose five recommendations for building resilience into government using data science:

1. Provide ethical guardrails for data science in government.

2. Invest in ready-to-go data infrastructure and models.

3. Distil essential causal mechanisms from complex systems.

4. Utilise collective modelling approaches.

5. Work across boundaries to share insights between domains.

Following these recommendations will place governments in a better position to tackle the growing list of existential problems that loom, from the next pandemic to global environmental collapse.

1. Introduction

Shocks such as energy crises, pandemics, trade wars, or stock market crashes often reveal weaknesses in policy-making systems. Under conditions of stress, any fragmentation, inflexibility and lack of agility in the machinery of government becomes apparent: fragile decision-making processes grind to a halt precisely when they need to be most efficient and adaptive. For this reason, shocks are often followed by calls for organisational reform and improvements to government decision-making processes to improve resilience. Precipitated by the 2007–08 financial crisis, growing concerns about socioeconomic and environmental stability, and the COVID-19 pandemic, such calls have intensified in recent years.

'Resilience' now steadily appears at the top of policy makers' concerns.[1,2] Yet, it remains as elusive as ever. The need for principled ways to build resilience into governments' decision-making processes is the motivation for this white paper.

Resilience is defined as the ability to adapt to changes in circumstance or recover quickly from disturbances.[3] For instance, an ecosystem is resilient if it is able to quickly return to a prior state of equilibrium when disturbed by factors such as transient environmental fluctuations or human activity.[4,5] Similar notions have been used to analyse the resilience of socioeconomic and financial systems.[6]

In this white paper, we will apply these notions to governments' decision-making systems, and outline how modern data science methods can make these systems more resilient and better able to adapt to change.

A resilient government should prioritise stability and adaptability in order to withstand shocks. As an ideal, a resilient policy-making system is one that is able to flexibly draw on expertise, including technologies, tools and methods, to make well-informed decisions despite vagaries in circumstance. Governments are starting to realise that modern methods of data science have enormous potential to boost their expertise. In a policy context, data science tools can be used to detect and measure social, healthcare and economic phenomena; simulate policy scenarios and evaluate their outcomes; make realistic predictions about the future; and personalise public services.[7] Modern data science methods also have the potential to embed resilience in governments' decision-making systems, providing policy makers with faster and more responsive ways of designing interventions.

Section 2 of this white paper outlines our vision for using data science to make policy-making more resilient. In Section 2.1, we explain how governments lost resilience and how this has affected their ability to capitalise on data science. Based on the experiences of AI for science and government (ASG) researchers under the 'Shocks and resilience' (S&R) theme at The Alan Turing Institute, we then outline important components of public sector data science that can help to build robust and resilient decision-making back into government, focusing first on ethical foundations (Section 2.2) and then on the data science methods themselves (Section 2.3). In these sections, we share the learnings from our experiences in the S&R theme through a series of case studies and use them to inform the five recommendations for data science in resilient government provided in Section 3.

2. How can data science make policy-making more resilient?

In recent decades, the private sector has made rapid progress in using data science to solve hard problems. This work has typically focused on using tools such as deep learning to complete well-specified, yet difficult and time-consuming tasks that traditionally required human intelligence.[8] For governments aiming to prioritise resilience over cost-cutting, this may not be the best approach. This is because resilient decision-making means solving very different kinds of problems; problems involving trade-offs for which there may be no “correct” answer. For instance, how to allocate resources for climate change adaptation in an uncertain future, or how to reduce hospitalisation rates in an epidemic while protecting the economy. Often, these kinds of problems mean bringing together data and expertise from across different disciplines, which can be very challenging. Therefore, the primary aim of public sector data science should not be to replicate human capabilities or to reduce costs but to boost governments’ expertise by collecting, linking and modelling heterogeneous data, and mediating between different areas of human expertise.

To meet this challenge, we propose a vision for data science in resilient government, articulated in Sections 2.2 and 2.3 and distilled in the five recommendations outlined in Section 3. First, though, in Section 2.1, we ground our argument in a historical perspective on resilience as a value and how different value systems have shaped governments’ responses to shocks, from economic crises to pandemics.

2.1 Prioritising resilience as an administrative value

Policy-making systems are characterised by distinctive values that are initiated by the administrative philosophy that informed their design or reform. Over time, these values become embedded in decision-making, through organisational practices, culture and technology. In a now highly cited paper, the leading public administration scholar Christopher Hood outlined three overlapping families of values that underpin administrative design.[9] They are:

1. Economy and leanness of purpose: where the standard of success is frugality of resource use and where “the central concern is to ‘trim fat’ and avoid ‘slack’”.

2. Resilience and robustness: where the standards of success are reliability and adaptability, and where “the central concern is to avoid system failure, ‘downtime’, [and] paralysis in the face of threat or challenge”.

3. Fairness and honesty: where the standards of success are public trust and confidence and “the central concern is to ensure honesty, prevent ‘capture’ of public bodies by unrepresentative groups, and avoid all arbitrary proceeding”.

Hood argued that while all three sets of values are potentially desirable and the same organising principle might satisfy any two, no management design can satisfy all three. The idea that there are a limited number of values that underpin administrative reforms, that cannot all be prioritised or achievable simultaneously, is a consistent theme in public administration.

State decision-making is most often characterised by the second set of values: resilience and robustness. This is why public sector organisations are often brought in during crisis situations. After the Second World War, resilience was particularly favoured. Both UK and US governments became innovators and leaders in administrative computing (building in part on Alan Turing’s scientific advances during the war). The technology of the time – huge, mainframe computer systems, based on symbolic code rather than being data-driven – were well-suited to the processes and practices of large-scale administrative bureaucracy. These systems were used to build reliability and resilience into organisational capacity, and power the growing functionality of the modern state.[10,11]

However, just as shocks and crises highlight the need for resilience, they engender the need to mitigate inequity and unfairness. The values of fairness and honesty, originally geared at distinguishing a public sector ethos from that of the private sector, are central and traditional in public management. In response to the rampant inequality exposed and reinforced by both world wars, fairness and equity were infused through the burgeoning organisational apparatus of the UK national health service and nascent welfare state, with their promise to look after all citizens ‘from cradle to grave’. Inequality had become so stark – in terms

of employment and income, for example – that it threatened to lead to instability, which in turn threatened resilience.

In the 1980s, though, many western governments changed focus, prioritising economy and leanness of purpose over all other administrative values. The dominant paradigm for administrative reform at this time was New Public Management (NPM), which aimed to transfer management practices developed for business to the public sector. NPM involved competition (through outsourcing), incentivisation (through performance pay and management) and disaggregation (breaking up large departments into agencies and public–private partnerships).[12,13] In countries that pursued NPM enthusiastically, organisational capacity was deliberately reduced: 'slack in the system' was diminished or eliminated, which, in turn, eroded resilience. Government technology projects now became more about automating routine tasks to reduce staffing costs than about innovating. Meanwhile, the disaggregation of government departments reduced their ability to address problems spanning multiple sectors or to make coherent policy in a globally connected world.

The widespread and sustained move towards economy and leanness of purpose as core administrative values led to governmental structures that were inherently fragile. This fragility has been clearly exposed by the COVID-19 pandemic. The crisis put the spotlight on interconnection: the SARS-CoV-2 virus spread globally through social networks; containment measures such as travel restrictions and lockdowns affected supply chains and had knock-on effects across the world. As the pandemic progressed, it became clear that many governments did not have the holistic data infrastructure and modelling capabilities needed for decision-making in this context. Many lacked the technological capacity to understand the pandemic's trajectory and build robust testing and tracing systems. Perhaps more significantly, they lacked the tools needed to understand healthcare and economic trade-offs and therefore evaluate policy options that benefit one area at the risk of another.[14]

Post-pandemic, many governments are in the process of rethinking their administrative values. Retraining their focus on resilience and fairness could also inspire governments to change how they use technology, switching from cost-cutting back to innovating and strengthening their expertise. Whilst these are the same values prioritised by governments in the post-war period, the technologies are now radically different. Advances in data science and data-driven technologies offer insights that could help policy makers address some of the most difficult problems facing society and change government decision-making for the better.

A resilient policy-making system is able to weigh the impacts of decisions on different sectors and adapt to new information as it arises. It is able to integrate and harmonise information from numerous distinct sources – such as healthcare, economic and social indicators – and balance the effects of policy decisions that may be beneficial in one area, but costly in another.

How can we use data science to help build such a system? Mathematical or computational models can be extremely valuable for formulating our knowledge and assumptions about the world into a rigorous framework that allows exploration of the logical consequences of different policy decisions.[15] Machine learning methods, meanwhile, are powerful tools for spotting patterns in heterogeneous sources of data.[16] Hence, governments should make better use of data, models and machine learning methods to inform their policy choices. In the following sections, we outline the ethical foundations (Section 2.2), and the data science tools and methods (Section 2.3), required to build more resilient policy-making systems.

2.2 Data science foundations for more resilient policy-making systems

Recognising that the values of resilience and robustness are entwined with the values of fairness and honesty, in this section, we outline the ethical foundations that should form the basis for a resilient policy-making system informed by data science. We illustrate our vision with case studies describing key projects carried out by ASG researchers under the S&R theme at the Turing.

As noted in the 'values' discussion in Section 2.1, shocks and crises can bring rising levels of inequality and reinforce structural inequalities that can lead to social instability, thereby undermining policy makers' ability to make robust decisions. For example, lockdown and self-isolation orders issued by governments during the COVID-19 pandemic were more difficult for lower income households to comply with due to their inability to absorb the associated income losses. Therefore, for policy makers to avoid undermining the resilience of public health measures and ensure these measures had the desired effects, resources needed to be appropriately redistributed towards lower income households. The pandemic also revealed the need for transparency in decision-making and administrative practices. Lack of transparency can erode the legitimacy of policy decisions, particularly where they include measures such as lockdowns, which were viewed as oppressive in many countries, further augmenting instability.

Thus, resilient government cannot prioritise the values of resilience and robustness alone; the values of fairness and honesty (or transparency) are crucial to avoiding a situation where inequality threatens government stability and resilience. So, as we build the foundations for more resilient government using data science, we must **provide the ethical guardrails** to ensure that data science is used in safe and ethical ways (see Recommendation 1 in Section 3). Traditionally, the values of fairness and honesty were institutionalised in mechanisms for appeal, public reporting requirements, independent scrutiny systems and attempts to socialise public servants in ethical principles. In the same way, when data science is being used in a central role in government, its design, development and deployment must be infused with the kind of values that made up this 'public sector ethos'.

ASG and Turing researchers more widely have worked hand in hand with government departments to develop ethical principles, frameworks, codebooks and standards to help integrate the values of fairness and transparency into data science. Based on the FAST principles of Fairness, Accountability, Sustainability and Transparency,[17] our frameworks set the standards for designing, developing and deploying data science in ethical ways. (See Case study: Setting the standards for ethical AI.)

Case study: Setting the standards for ethical AI

Through guidance that holds ethical principles at its core, ASG researchers are putting in place processes and standards to mitigate against harm from data-driven technologies.

The official UK government guidance on building responsible AI systems in the public sector was developed by Turing data ethics researchers in collaboration with the Office for Artificial Intelligence, Government Digital Service and Ministry of Justice. This internationally recognised guidance, 'Understanding AI ethics and safety' (2019), has already been put into practice by at least a dozen different UK government departments. It details good practice guidelines for designing and implementing ethically sound AI systems that first and foremost consider the humans who use and are affected by them. Turing researchers are now collaborating with government and public sector partners to update the guidance and co-create a bespoke training programme that will embed it within public sector AI projects.

The guidance has also become the wellspring for the values and principles shaping other Turing projects, including Project ExplAIn. In Project ExplAIn, ASG researchers worked with the Information Commissioner's Office on 'Explaining decisions made by AI' (2020), which offers practical advice for organisations on explaining how they use AI systems to make their decisions. Developed in collaboration with members of the public, scientists and industry experts through workshops and roundtables, the guidance is now being used by the UK government to develop AI assurance processes for ensuring the trustworthiness of AI systems and guarding against their potential harms.

The Health Index

The UK's Office for National Statistics (ONS) is developing a National Health Index: a simple and consistent measure of the health of the population through time, at local and national levels. Health scores are produced by combining data from multiple health-related and socioeconomic indicators.

Given the broad implications for policy-making – for instance, in analysing the health effects of shocks like pandemics and responding to them – the index must use the most transparent methods possible to provide reliable insights. To this end, ASG researchers completed a rigorous statistical assessment of how it is put together. The ONS is currently in the process of implementing their recommendations.

They demonstrate a citizen-focused approach to data science, which directly involves the people affected by use of data science technologies in the process of shaping standards to guide their safe use. Meanwhile, the Turing's practical guidance for organisations on 'explainability' emphasises the principles of fairness and transparency in communicating how AI systems and people's personal data are used to assist in decision-making.

Under the S&R programme, ASG researchers have also worked closely with government departments involved in embedding transparency into their data science projects, as in a collaboration with the UK government's Office for National Statistics (ONS) on a National Health Index (see The Health Index) for England. This project, which is intended to support decision-making relating to people's health across the UK, emphasises the careful balance to be struck between usefulness and transparency in the data science methods used for policy-making.

2.3 Data science methods for more resilient policy-making systems

In this section, we describe some data science methods and approaches to modelling that can be of benefit to resilient policy-making, illustrating our vision with case studies describing key projects carried out by ASG researchers under the S&R theme.

Firstly, when shocks occur, governments must be able to access tools, methods and technologies that will allow them to intervene efficiently to promote stability. This means having in place **data infrastructures and models that are 'ready-to-go'** as required, supporting timely access to data and the tools needed to analyse that data (see Recommendation 2 in Section 3). The challenge for governments seeking resilience is to build data infrastructure such that models can be continually updated based on accurate, up-to-date data, and can, in turn, provide rapid, accurate recommendations to decision makers.

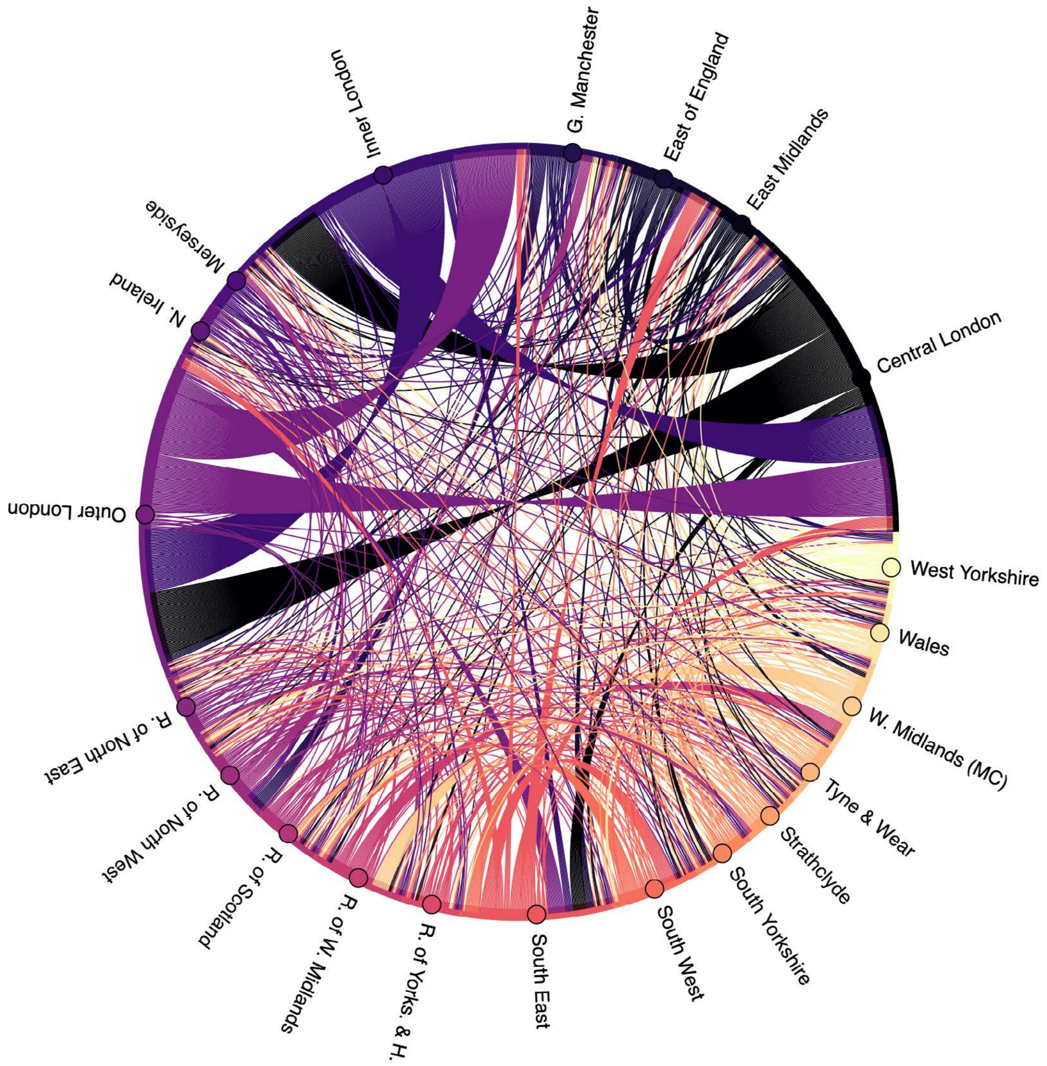


Figure 1: Simulated labour flows between different geographical regions (shown as different coloured dots) within the UK. Flow colour corresponds to the region from which the flow originated.

Case study: Anticipating the effects of labour market shocks

ASG researchers developed cutting-edge models of the labour network to help policy makers predict how the market might react to economic shocks and policy interventions.

Developed in collaboration with the UK government's former Department for Business, Energy & Industrial Strategy (BEIS), the models use an agent-based approach to modelling to simulate movements in the job market in granular detail. This approach is robust to an unstable labour market impacted by shocks such as the COVID-19 pandemic, which can fundamentally change the labour market by impacting how people make employment decisions – for instance, by increasing opportunities for home-working. Instead of assuming a fixed structure, as models based on historical data have typically done, agent-based modelling simulates thousands of employees from real labour data and uses them to explore a network representing labour market flows, thus determining the market's structure as part of the simulation. Work under the S&R theme shows that these models can anticipate changes in response to hypothetical shocks, such as a sudden dramatic decrease in wages in certain occupations.

The researchers are now tailoring the open-source code for their modelling framework to help BEIS run its own simulations. More generally, this framework provides powerful tools for navigating uncertainty in labour markets around, for example, transitions towards green jobs or increasing automation. By simulating alternative scenarios they can help policy makers assess the effectiveness of different interventions, like upskilling or increasing wages, for moving people along paths to suitable employment.

A key technology here is agent computing, which allows us to build models that can simulate both the effects of a shock to a policy system, as well as the effects of a specific intervention. The approach creates ‘agents’, representing individuals who explore a network or ‘world’. For example, agent-based models developed under the S&R theme are capable of simulating people’s movements across entire labour markets in granular detail, as well as the effects of shocks and interventions to those markets (See Case study: Anticipating the effects of labour market shocks and Figure 1). Agent computing has also become popular as a tool for transport planning and providing insights for decision makers in disaster scenarios such as nuclear attacks or pandemics.[18]

In the case of a pandemic (see Pandemia), agent-based models allowed policy makers to both understand some of the longer-term effects – including of measures taken to limit the spread of infection, such as lockdowns – and to design policy interventions, such as furlough schemes, in an evidence-based way. These models enable policy makers to understand the implications of possible shocks and interventions without suffering unintended consequences, thereby building resilience into decision-making. During the COVID-19 pandemic, many governments implemented such measures with little evidence as to how they would work in practice. Whilst simulation techniques often did inform decision-making, these models were typically developed in haste and were fraught with uncertainties. For future resilient policy-making, the data infrastructure and models required to implement them must be established in advance of need.

More generally, policy-making could make use of ‘digital twins’. A digital twin is a virtual representation of a physical system or process[19] that is continually updated from data collected via monitoring of the real system. As such, it may be used to make precise predictions, design improvements or plan robust interventions based on current

Pandemia

Working with members of the Turing’s Research Engineering Group, S&R researchers created Pandemia, an easy-to-implement, open-source framework for simulating disease dynamics across multiple geographic regions, under different policy settings.

Pandemia is constructed to allow parallel processing of large volumes of data, making it computationally very efficient – the behaviour of hundreds of millions of people (‘agents’) can be simulated on a laptop. It helps policy makers to explore how multiple social, economic and healthcare policy decisions will interact with those in neighbouring regions and affect global disease dynamics, without needing access to costly or specialist computational resources.

data. Digital twins are increasingly used for emergency planning as well as a wide range of complex scientific and control problems,[20–22] with ASG researchers at the forefront of research in this rapidly advancing field.[23] Whilst not yet widely used in policy contexts, we anticipate that by connecting models directly to the socioeconomic systems that they describe, digital twins will provide policy makers with a powerful suite of tools to intervene efficiently and robustly based on current data. Because digital twin methodology is in its infancy and most methods are still bespoke, realising this potential will require new tools and methods to produce digital twins at scale,[24–26] with policy applications specifically in mind.

Next, we highlight the need for resilient policy-making to derive general lessons from particular circumstances, and thereby remain primed to respond in an agile way to change. Highly optimised models, designed to answer narrow policy questions of limited significance, are not necessarily well-placed to respond with such agility and so may have limited utility. To make the most of modelling, we may therefore need to re-frame what we require from it. Rather than using models to assess the likelihood of specific possible outcomes – or make dubious attempts to predict the unpredictable – models can be used to formulate general principles that hold whenever certain broad assumptions are fulfilled. Such principles are often simpler, easier to infer from sparser data, more straightforward to convey and may be of greater practical use to policy makers than detailed predictions.

These issues may be collectively summarised as a **need to build models that allow us to better understand causality**[27,28] (see Recommendation 3 in Section 3). This is a challenge at the forefront of modern statistics and machine learning that has widespread importance beyond policy.[29–31] Yet, understanding causality is arguably particularly important for policy-making for two reasons. First, causal models allow the weighing of counterfactuals – answers to 'what if'

questions about how different scenarios might play out. For example, the labour market models developed under the S&R theme are capable of answering these types of questions, allowing policy makers to predict how the labour market will react under different shock scenarios that affect jobs and wages (see Case study: Anticipating the effects of labour market shocks). Models capable of addressing counterfactual scenarios are central to robust decision-making in complex situations because they enable the design of precise interventions with predictable consequences.[32] Second, models that allow policy makers to distil essential causal mechanisms are more likely to be interpretable, and therefore explainable, than 'black-box' methods. As noted in Section 2.2, in sensitive policy settings that require public trust, this explainability is of substantial benefit. Therefore, we anticipate that developing interpretable methods for better understanding causality in different policy domains is likely to be considerably more useful to resilient policy-making than improving the predictive

Case study: Ensemble modelling for robust predictions in changing circumstances

Since 2011, general practitioners (GPs) in Scotland have used a simple scoring system to identify patients at high risk of emergency admission. The SPARRA (Scottish Patients At Risk of Re-admission and Admission) tool provides monthly, individual risk scores for around 80% of the Scottish population, enabling a preventive approach to healthcare centring on reducing patient risk – informing, for example, medication adjustments and targeted referrals – and allowing GPs to quickly assess the health status of new patients.

SPARRA version 4, developed by ASG-funded researchers in partnership with Public Health Scotland and due to be deployed in 2023, refines the previous tool (version 3) using cutting-edge machine learning techniques to better identify at-risk patients. The researchers took an ensemble modelling approach combining six different types of models – including the model used in version 3 – to boost performance compared with any individual ensemble member. This gives an improvement in accuracy equating to hundreds more patients being correctly identified as at-risk, whilst protecting against erroneous results that occur due to the way individual models work.

An ensemble modelling approach is also used by IceNet, an AI tool created by ASG and British Antarctic Survey researchers to enable rapid, more precise predictions of Arctic sea ice conditions. IceNet takes its forecasts from 25 separate ensemble members, giving a more accurate result than any single forecast and tempering any anomalous predictions. Better sea ice forecasting will enable more appropriate and timely responses to threats to wildlife and Indigenous peoples in an environment under pressure from climate change.

accuracy of ever more complex, and context-specific, models.

Whilst it is often preferable to distil understanding into clear causal principles, it may not always be possible to straightforwardly construct one simple and transparent model for policy-making purposes. In some cases, complex problems may require a **collective or 'ensemble' modelling approach** that brings together different models to tackle a common problem (see Recommendation 4 in Section 3).

Such ensemble modelling has been widely adopted for climate modelling,[33–35] macroeconomic predictions[36] and financial forecasting.[37,38] It also forms the basis of modelling approaches developed by ASG researchers to identify patients at risk of emergency hospital admissions and for rapid, more accurate sea ice forecasting (see Case study: Ensemble modelling for robust predictions in changing circumstances). The key advantage of this collective approach is that often none of the models needs to be highly accurate, yet predictions of the collective as a whole can be.[39] For example, the collective modelling approach developed at the Turing to predict patient emergency emissions improves substantially on the previous (single) model used to produce predictions, as well as on any individual model employed in the ensemble.

Properly constructed, ensembles can often make powerful predictions by combining the output of numerous (and often simple) models. They are valuable for resilient policy-making because they often produce more accurate results under conditions of substantial uncertainty, and can be adapted and improved under changing circumstances by adding or removing models from the ensemble. They can also be used to combine models developed in different sectors or by different teams, with each ensemble member taking a different world view or making different assumptions – a valuable approach for addressing complex, multi-sector policy problems. In the US, for example, the Centres for Disease Control and Prevention produces its influenza forecasts through ensemble modelling,[40] collaborating with different forecasting teams, some of which take their data from different sources but all of which use different methods to reach their results.

Lastly, we underline the importance for resilient policy-making of **working across traditional boundaries and sharing insights between domains** (see Recommendation 5 in Section 3). The design, development and implementation of effective tools and models for resilient policy-making must be guided by strong, interdisciplinary collaborations between decision makers and experts from across multiple different domains – from mathematicians and data scientists to ethicists and social scientists. Such interdisciplinary working can be incentivised by investing in collaborative spaces that sit outside the bounds of traditional academia.

Case study: Multidisciplinary tools to enable modelling across domains

The COVID-19 pandemic inspired a surge in multidisciplinary collaboration as researchers responded to the Royal Society's call to enhance pandemic modelling capacity. At the Turing, some of the models and tools developed as a result of these collaborative efforts, centred initially around disease modelling, have already found use in other domains. The Synthetic Population Catalyst (SPC) emerged as a shared, easy-to-use tool developed by ASG researchers to help scientists in need of data to feed population models.

Population modelling can support resilient policy-making across diverse areas, from health and the environment to transport and the economy. However, due to privacy issues, it can be hard to acquire useful datasets, so researchers now often use 'synthetic data' instead. This artificial data is generated from real sources but does not contain sensitive information linked to real people. The SPC tool quickly combines data from official UK data sources, for selected areas, to supply synthetic population data in a format that can be used to power complex demographic models. As a thoroughly documented, open-source tool, it allows for reuse and adaptation across a broad range of policy domains. For example, researchers can collaborate with SPC's creators to add new variables, via new data sources, to suit their individual modelling needs.

ASG researchers are using synthetic data generated by the SPC tool to feed a model for analysing the effects of climate-related heat exposure on health. This model will, in turn, feed the University of Exeter's Local Climate Adaptation Tool (LCAT), designed in collaboration with local authorities to support evidence-based policy-making at the local level.

Understanding economic complexity

Existing economic indices can guide policy makers on which industries to invest in to increase growth. Now, new methods developed by S&R researchers can also suggest what form these investments should take, providing recommendations for resilient policy-making through deeper analysis of production processes involving complex networks of suppliers and distributors. Their methods transfer insights from mathematical frameworks designed for understanding the human brain. Recent analysis using the methods shows that innovative technologies and production processes cannot thrive merely on creativity – measured as the synergy between inputs in production processes. They require redundancy too, meaning, for instance, having multiple suppliers for the same product to shockproof against global supply issues.

The highly collaborative environment at the Turing, for example, has led to the development of a tool that can support population modelling across numerous policy domains (see Case study: Multidisciplinary tools enable modelling across domains). Modelling based on this tool is already being used to support local policy-making on climate change, but the tool itself can be adapted and updated for use within any policy sector.

When constructed with care, multidisciplinary tools and models can provide a powerful 'glue' that brings together different disciplinary perspectives and boosts governments' expertise. The challenge is to build multidisciplinary communities of practice and systems that are able to robustly and ethically integrate available data and information from different policy and scientific domains, and provide useful insight despite uncertainties.[15]

The value of interdisciplinary working becomes particularly apparent in situations where information gained from solving one problem can be passed directly to another, related problem area. Under the S&R theme, for example, ASG researchers applied methods developed for studying the human brain to understanding economic complexity (see Understanding economic complexity).

Meanwhile, in a branch of machine learning known as 'transfer learning', substantial gains can be made by leveraging prior knowledge from a data-abundant source domain to learn new concepts in a data-sparse target domain. Because the problem of limited data is ubiquitous, transfer learning has been used to effectively address data sparse modelling problems in numerous areas.[41] In policy-making, these methodologies could be used to transfer insights between, for example, different countries or related specialties within healthcare, potentially providing significant benefit to policy makers of the future.

3. Recommendations

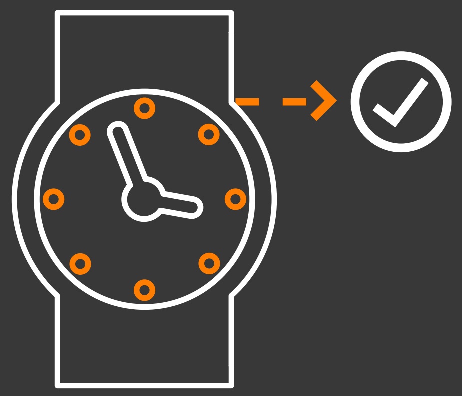
Based on our wide-ranging experiences in the ASG programme under the S&R theme, we propose the following five recommendations for building resilience into policy-making:

1

Provide ethical guardrails for data science in government

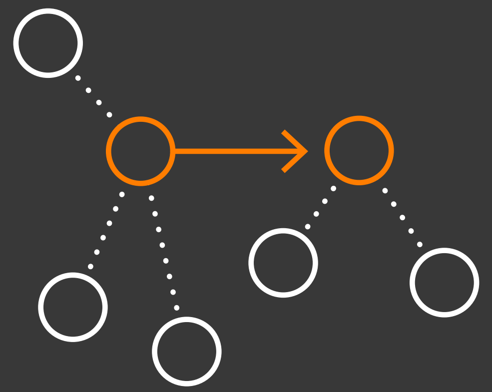
2

Invest in ‘ready-to-go’ data infrastructure and models



3

Distil essential causal mechanisms from complex systems



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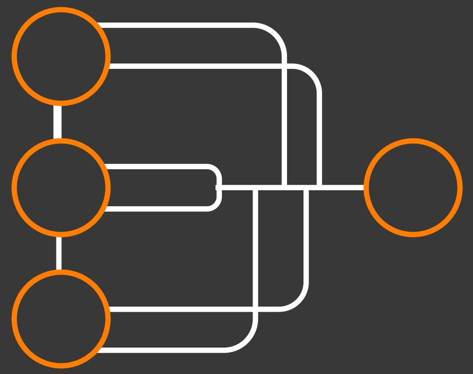
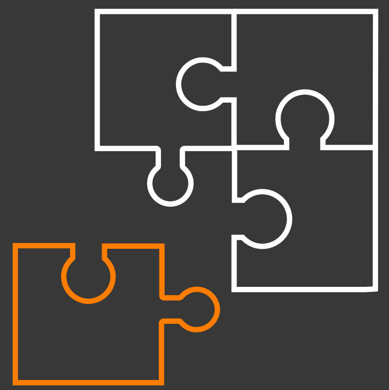
Utilise collective modelling approaches



5

Work across boundaries to share insights between domains



1 **Provide ethical guardrails for data science in government**

Develop frameworks to embed the FAST (fairness, accountability, sustainability and transparency) principles into the design, development and deployment of data science in government. These frameworks should incorporate insight from participatory processes – such as citizens' juries and roundtables – involving those affected by the use of data-driven technologies.

2 **Invest in 'ready-to-go' data infrastructure and models**

The data infrastructures and models required to access and analyse data, informing rapid decisions in times of crisis, should be established in advance of need. Models that allow policy makers to explore the effects of policy interventions before the interventions are implemented will help to avoid unintended consequences.

3 **Distil essential causal mechanisms from complex systems**

Resilient policy requires understanding of how myriad socioeconomic factors affect each other. Models that distil essential causal mechanisms allow the impacts of interventions to be rigorously assessed. For policy-making, they should be preferred over black-box models to ensure interpretability and transparency, particularly in high-stakes decision-making.

4 **Utilise collective modelling approaches**

Robust decisions can be made by using ensembles of models in which each model takes a different path to tackling a hard problem. Policy makers should take advantage of this 'wisdom of crowds' approach to create adaptable models capable of producing more accurate results under uncertain conditions.

5 **Work across boundaries to share insights between domains**

Interdisciplinary working should be embraced to facilitate the sharing of tools, techniques and knowledge between disciplines, and to identify where information and methods developed in one domain can be applied in another.

4. Conclusions

Governments the world over are seeking more resilient policy-making systems to help address myriad healthcare, social, economic and environmental challenges. In this white paper, we have argued that to build resilience, a reform of data science for government explicitly designed to tackle complex public sector challenges is needed.

Many modern data science methods can be extraordinarily powerful for solving problems with well-defined objectives, and this focus has produced highly successful and innovative new technologies. But in the heterogeneous and multi-purpose public sector, the more nebulous question of how to make 'good' and 'timely' decisions, particularly those that prioritise resilience, is a more challenging proposition.

We suggest that rather than focusing on reducing costs through automation of what humans can already do well, data science reforms should focus on doing what humans cannot do well: addressing difficult, interconnected problems with many possible solutions through the harmonisation of data, knowledge, and expertise from different domains.

This white paper presents a vision for how data science can contribute to more resilient government and policy-making, along with a set of five recommendations. These begin with putting in place 'guardrails' to guide the safe and ethical use of data science within government, and establishing 'ready to go' data infrastructure and models that policy makers can use for rapid data analysis and decision-making in times of crisis. Our third and fourth recommendations highlight modelling approaches that can be particularly helpful for resilient policy-making: models that can help to distil essential causal mechanisms from complex systems, and ensemble (collective) modelling. Our final recommendation highlights the value of interdisciplinary working for addressing interconnected policy problems. Realising our vision will require reconsideration of how resources are devoted to data science research and development.

We envisage a future in which data science is used to support specialist human expertise to pose and tackle difficult questions – questions that may be vague and might not have clear 'correct' answers – thereby fairly balancing the views and interests of diverse stakeholders, and weighing the impact of policy choices on society as a whole.

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