

Evidence-informed policy-making in a data-driven age: The role and limits of official statistics

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Abstract

Official statistics have long provided a foundation for evidence-informed policy-making, offering professionally independent, quality-assured and transparent evidence to support democratic decision-making. Yet the contemporary policy environment presents statistical systems with a difficult set of pressures. Demand is growing for faster, more granular and more actionable evidence, particularly during crises, while policymakers increasingly draw on dashboards, models, artificial intelligence and non-traditional data sources. These tools can improve timeliness and analytical capacity, but they also raise risks relating to bias, opacity, representativity, uncertainty and accountability. This paper examines the evolving role of official statistics in this context, arguing that their value lies not in automating or determining policy choices, but in anchoring them. It distinguishes between evidence-informed and data-driven decision-making, warning that the latter may imply a technocratic shift in which data appear to substitute for human judgement. Drawing on Irish and international examples, the paper considers the institutional, methodological and democratic challenges facing official statistics, including data access, public trust, communication, artificial intelligence and the post-truth information environment. It concludes that official statistics remain essential democratic infrastructure: they should inform decisions, clarify trade-offs and support accountability, while remaining subordinate to context, deliberation and judgement.

Keywords: artificial intelligence, data-driven, data governance, data quality, democratic accountability, evidence-informed, Ireland, official statistics, policy-making, public trust, statistical systems.

Introduction

According to Boaz et al. (2018), the term ‘Evidence Based Policy making’ emerged in the United Kingdom in the run up to the government, headed by Tony Blair, being elected in 1997. The idea itself, however, was not new, rather it was a new label for a practice dating back centuries. Individuals, corporations and states have long used evidence, often provided by statistics, to inform their decisions. From an Irish statistics perspective, although implicit in earlier strategies, it was the National Statistics Board (NSB) *Strategy for Statistics 2003–2008* (NSB, 2003) that first referred to evidence-based policy.

Over time, official statistics have become a cornerstone of evidence-based or evidence-informed policy-making as they provide professionally independent, quality-assured, and transparent evidence to guide decisions and track efficacy. The terms ‘evidence-based’ and ‘evidence-informed’ are often used interchangeably, with the distinction treated as largely stylistic. In this paper, however, the choice of evidence-informed is deliberate and used throughout. The choice reflects an important nuance: policy decisions are not determined by evidence alone, politicians and civil servants must also weigh public perceptions, institutional constraints, competing priorities, and political realities. While official statistics or other robust evidence should inform policy choices, it would be naïve to assume that they are the only input. The term ‘evidence-informed’ therefore better captures the role of evidence in real-world policy-making: essential, but not exclusive.

In a policy environment increasingly shaped by dashboards, non-traditional data, artificial intelligence and algorithmic systems, there is a growing risk that the role of evidence may shift from informing decisions to determining them. While these tools can improve timeliness and analytical rigour, they can also embed bias, obscure uncertainty, weaken representativity, and displace human accountability. This paper argues that the value of official statistics lies not in automating decision-making, but in anchoring it: evidence should support democratic judgement, not substitute for it. In parallel, there is an increasing risk that in a ‘post-truth’ world, evidence may become extraneous to decisions. In fact, Davis (2017) has concluded that official statistics are losing the battle for relevance, and this decline is at the heart of the ‘post-truth’ crisis. This paper argues that the acceptance of evidence is essential if the notion of a deliberative

public discourse is to survive. In Ireland, both the NSB 2021–6 strategy (NSB, 2021) and the *CSO Data Strategy 2026–2028* (Central Statistics Office (CSO), 2026) implicitly speak to many of these issues.

The first section of the paper traces the evolution in the demand for official statistics over the twentieth century, prompted in particular by industrialisation, global crises, demands for economic management, and public accountability. The second section examines the distinctive role of official statistics in policy-making, with particular attention being given to professional independence, impartiality and the challenges of ensuring that data are representative and fit-for-purpose. This is followed by a discussion of the pressures experienced by those working in the area of official statistics who must balance a wish to support policy analysis, while also being mindful of the risks of bias, opacity and oversimplification. These pressures are discussed under five headings: timeliness, crisis conditions, modelling, dashboards and artificial intelligence. The final section concludes by reflecting on the growing shift from evidence-informed to data-driven decision-making, and on why preserving the role of human judgement is essential to both sound policy and democratic legitimacy.

The evolution of demand for official statistics

A wide range of phenomena and events have prompted the increased demand for evidence and statistics. One important development was the understanding that risk and uncertainty could be understood and managed. This idea emerged alongside the secularisation of society, and the belief that people had agency, and therefore responsibility, for their own lives and decisions (Bernstein, 1996; Rostow, 1959). People needed information to inform those decisions. Agar (2001) also identifies the two historical tidal waves of globalisation – industrialisation and empire – as major forces behind this demand, as expanding trade, banking, financial systems, and the management of credit and debt all required more systematic information.

Two events in the early twentieth century had a very significant impact on the demand for statistics: the Great Depression and Second World War. In response to the Great Depression, Franklin D. Roosevelt's 'New Deal' required a level of statistical sophistication that had not previously existed. Policymakers needed to understand not only the size and structure of the economy, but also the distribution of income and wealth, and the likely effects of redistribution. This shift away from laissez-faire economics towards

more interventionist social and economic policies, including the countercyclical economic management associated with Keynesianism, was accompanied by a growing need for evidence (Fogel et al., 2013).

Before the Second World War, economic planning was still largely descriptive, making relatively little use of quantitative evidence (Masood, 2016). The war and subsequent reconstruction efforts marked a step change in the demand for quantitative evidence. The global scale and unprecedented mobilisation required a greater degree of planning than previous engagements, involving the industrialisation of cryptanalysis, the development of transport and logistical systems to secure and distribute materials and commodities, the organisation of labour, the imposition of price controls, and the balancing of domestic and war economies. This dramatic expansion in the use of data led Patinkin (1976) to describe the war as a ‘statistical revolution’. Reflecting the new importance of statistics, the United Nations Statistical Commission was established in 1947 as one of the first commissions of the United Nations after the war.

Taylorism, or scientific management, that had driven the demand for data in industry in the early twentieth century, morphed into new public management in the 1980s and spread the culture of measurement and demand for statistics to the public sector. Accountability, performance measurement, and metrics became buzzwords among politicians and policymakers, as they were seen as guarantees of objectivity (Muller, 2018). The demand for rigour, for hard evidence, for transparency and impartiality also contributed to the demand for official statistics as the principles of scientific management and evidence-based decision-making became more embedded in public policy. Desrosières (2010) argues that this neoliberal model led to an ‘indicator culture’ that objectified statistics and fuelled their proliferation.

Today, official statistics are widely recognised as indispensable to decision-making in the design and implementation of economic and social policy, and as ‘fundamental to democracy, to democratic accountability, to checks and balances, to economic and social well-being, and to progress more broadly’ (Mink, 2022, p. 5). As they have in the past, evolving policy challenges continue to generate demand for new forms of data. At the time of writing, the impact of artificial intelligence on employment and productivity, access to rare earth minerals, supply chain disruption, energy security and deglobalisation are among the most pressing policy priorities.

Yet the growing importance of statistics in policy-making also raises important questions: what kind of evidence is being used, and on what terms? If statistics are to inform policy credibly, they must not only be timely and relevant but also be produced and interpreted with professional independence and transparency. This brings into focus a central issue in evidence-informed policy-making: the extent to which statistics can, or should, be regarded as neutral.

The role of official statistics in policy-making

The use of statistics to inform decisions rests on the ideal that figures can serve as neutral arbiters in political debate. Implicit in that ideal is the assumption that those statistics are of good quality and are produced impartially. Of course, impartiality and neutrality are not the same thing, and either can be compromised, whether deliberately or inadvertently.

Even when a statistic is produced impartially, it may not be neutral. Some argue, with justification, that there is no such thing as neutral information (Luce, 2017). Behind every statistic lies a chain of human decisions, many of them unstated and undocumented (Borgman, 2015; Rudder, 2014). Conscious and subconscious decisions are made about how to treat outliers, how to impute missing values, what level of aggregation should be chosen, and how concepts are translated into measurable indicators. The list of decisions is almost endless. In many cases, statistical theory does not provide a single unambiguous answer, and so the compiler must exercise judgement. The translation from words to numbers always involves assumptions and theories that may be obscured behind a veil of a technocratic objectivity (Fukuda-Parr & McNeill, 2019). As the title of Gitelman's book (2013) eloquently suggests *'Raw Data' Is an Oxymoron*.

The choice of indicator may reflect, whether deliberately or inadvertently, a particular political or economic ideology; it may also be an intentional attempt to control a narrative. Mahajan (2019, p. 110) notes:

measurement is never an innocent matter where as it were, the facts speak for themselves. What is measured, who finances and does the measuring, how data are collated, interpreted, and disbursed, harnessed to decision-making and program implementation, and how other measures and ways of collecting information are displaced – all these are contested matters

because they are linked with the specific orientation of institutions and policies, the outcomes that they aspire to, and the forms of knowledge that they privilege.

Strict neutrality may be unattainable, but disciplined impartiality, safeguarded by professional norms and law, is not. That distinction matters because conflicts of interest are always a risk when consumers of data become its compilers (MacFeely & Nastav, 2019). The reasons should be obvious. If not, Rosling et al. (2018, p. 236) provide a simple analogy: ‘a long jumper is not allowed to measure her own jumps’. Advocacy or ideology may motivate compilers to produce a preferred result or outcome. The purpose of official statistics, by contrast, is to provide information that is, as far as possible, free from political agenda. The impartiality, or agnosticism, of official statisticians is one of the defining strengths of official statistics. It is also, at times, one of their weaknesses.

The question of whether other actors can compile better statistics than official statisticians lies at the heart of the debate over whether centralised or decentralised statistical systems are preferable. Each approach comes with strengths and weaknesses. Centralised statistical systems are typically regarded as stronger in terms of independence and impartiality, and are often justified not only by efficiencies of scale but by their ability to safeguard professional autonomy. However, they can sometimes struggle to remain relevant if they are too far removed from policy debate. Decentralised statistical units face the opposite trade-off. Their proximity to policymakers often allows them to produce highly relevant statistics, reflecting a deeper understanding of the context, but it also exposes them to greater risks of political interference, including pressure to present ministerial policies in a favourable light or align publication practices with political considerations, thereby compromising credibility (PARIS21, 2005; MacFeely & Barnat, 2017). The strengths and weaknesses of these competing models are well-documented, including in the United Nations *Handbook on Management and Organization of National Statistical Systems* (United Nations Department of Economic and Social Affairs, 2025).

Ireland provides a useful example of a hybrid model. Despite the statistical authority being called the Central Statistics Office, a significant share of official statistics is produced by policy departments or specialised agencies, including the Department of Education and Youth, the Department of Health, the Department of Social

Protection, the Central Bank of Ireland, and the Environmental Protection Agency of Ireland. Statisticians working in statistical units embedded within policy departments of the Irish Statistical System (ISS), are for the most part, recruited and trained by the CSO in an effort to leverage the benefits of decentralised production, while mitigating its risks. This, in turn, underlines the importance of statistical laws, professional norms, and system-wide codes of practice.

In Ireland, the Statistics Act (Oireachtas, 1993) formally establishes the professional independence of the CSO. The accompanying standards for the ISS are set out in the *Irish Statistical System Code of Practice (ISSCoP)* (CSO, 2013). For European statistics compiled within the ISS, professional independence and impartiality are further protected by the Regulation (EU) 2024/3018 on European Statistics (European Commission, 2024) and by the *European Statistics Code of Practice* (European Commission, 2017). More broadly, official statistics produced in Ireland are produced in adherence with the *UN Fundamental Principles of Official Statistics* (United Nations General Assembly, 2014) and the Organisation for Economic Co-operation and Development (OECD) *Recommendation of the Council on Good Statistical Practice* (OECD, 2019), both of which stress the need for official statistics to be compiled free from political and external interference.

Even so, impartial statistics are not in themselves a guarantee of impartial policy design or implementation. PARIS21 makes the point succinctly (PARIS21, 2025): ‘What is used in policymaking are not data as such but a specific interpretation of data, and official statistics in particular often leave significant room for interpretation’. It is not unheard of for statistical information to be used to engineer or justify decisions that have already been taken – what might playfully be described as *policy-based evidence*. As the famous military historian A. J. P. Taylor reflected (1961, p. 120):

There is little evidence that the rulers of the democratic countries (or of the dictatorial ones for that matter) ever consulted their military experts in a detached way before deciding on policy. They decided policy first; and then asked the experts for technical arguments with which this policy could be justified.

This behaviour is by no means limited to military decisions. The benefits of evidence-informed decision-making only accrue if the

decision maker is open to considering the full range of options and lessons presented by the data before the decision is made.

Questions of neutrality and impartiality are only part of the challenge of evidence-informed policy-making. Even where statistics are produced professionally and without political interference, they may still be limited in terms of coverage, timeliness, and/or relevance to the policy question at hand. The issue, therefore, is not only whether statistics are impartial, but also whether they are sufficiently representative and fit-for-purpose.

Representativity and trade-offs

No dataset is perfect. Each has its limitations, gaps and biases, and users are always well-advised to understand those limitations and ask who produced the data, how and for what purpose. Official statistics are produced under the professional obligations of independence, impartiality and quality assurance, but the wider evidence market is increasingly crowded, with official statistics competing alongside a wide range of other data products. No doubt some of these data are of underlying good quality, but many are accompanied by little or no metadata, paradata or transparent methodological documentation, making it effectively impossible to assess their meaning, quality or fitness-for-purpose (MacFeely, 2020). Given that context, the maxim *buyer beware* applies, especially in public policy, where the responsibility ultimately lies with the user to ensure that the data they use in their analyses are fit-for-purpose.

These longstanding risks are being compounded by the rise of artificial intelligence. There is now ample evidence demonstrating that artificial intelligence (AI) systems can reinforce and amplify existing biases and stereotypes, often because they are trained on outdated, incomplete, or systematically biased data (United Nations Economic Commission for Europe, 2025). In public administration, this creates the very real possibility that discriminatory assumptions may be hard-coded into algorithmic systems, without clear traceability or meaningful recourse (MacFeely & Ward, 2025). Analysts must also exercise caution when using generative AI as a tool for statistical inquiry. Large language models can produce plausible but inaccurate or misleading responses when querying statistical databases or summarising complex evidence (Marawala, 2024; Livera, 2025). The resulting falsehoods are often affectionately characterised as hallucinations or, perhaps more accurately, as ‘machine bullshit’

(Morgan, 2025). What makes this so dangerous is that the results often seem so plausible. How can a reasonably literate, but inexperienced user, be expected to distinguish this fiction from fact?

From a policy perspective, the central issue is whether the data used to inform policy decisions adequately represent the population to which the policy applies. The perfect match between existing statistics and the policy question, while the ideal, scarcely exists. Analysts must therefore ensure they understand the goodness-of-fit and then consult their '*statistical conscience*'. In practice, this often means navigating trade-offs rather than identifying an unequivocal best measure.

One common trade-off is between national relevance and international comparability. Many statistics attempt to be both nationally representative and internationally comparable, with varying success depending on the statistic. Purchasing power parities, for example, require internationally standardised baskets that inevitably sit uneasily with national consumption patterns. In Ireland, perhaps the most prominent tension is found in the compilation of gross domestic product (GDP), where the presence of large multinational enterprises has compromised GDP's analytical value for both national and international purposes (CSO, 2016; OECD, 2016). While the pursuit of international comparability can at times diminish analytical value at the national level, adherence to international standards also brings important benefits: imposing intellectual discipline, facilitating comparisons, and protecting professional independence by making it more difficult for governments to interfere with concepts and methods for political convenience.

A second trade-off concerns consistency over time. One of the core objectives of official statistics is to produce a coherent time series so that real change can be measured reliably. In some cases, this involves relatively uncontroversial adjustments, such as converting nominal estimates to real estimates through the use of deflators, although even here the choice of deflator can itself be contentious. In other cases, methodological improvements can enhance one analytical purpose while weakening another. For example, quality adjustments applied to products in consumer price indices, including hedonic methods applied to information and communication technology products or cars, may improve inflation measurement while making those same indices less useful as measures of cost of living. Here again, the task of the analyst is not to search for the perfect statistic, but to select the most appropriate one for their analytical purpose.

In the end, impartiality, representativity and fitness-for-purpose may still not be enough. In practice, these concerns are often inseparable from the problem of timeliness, especially in times of crisis, when decision makers demand evidence before complete or fully validated statistics are available. It is in these circumstances that the limits of official statistics are most clearly exposed, and where models and experimental data come into their own.

Crises and models

In 1785 the poet Robert Burns laughed at the ‘best laid plans of mice and men’. Years later Harold Macmillan reflected on this political reality when he laconically noted that governments must deal with ‘events, dear boy, events’. One longstanding criticism of official statistics concerns their timeliness and inability to deal with ‘events’. While the timeliness of many key statistical outputs continues to improve, users are increasingly demanding real-time data. For many routine scenarios, it is not clear why real-time data are required, nor whether such demands would survive objective cost–benefit analyses. During emergencies or crises however, decision makers may legitimately require real-time or close to real-time data.

Emergencies, shocks or disruptions are contexts in which official statistics – primarily designed to provide consistency and comparability over time and across regions – often struggle to adapt with sufficient speed. This is unsurprising, as these shocks typically bring with them new phenomena, such as the pandemic caused by coronavirus disease 2019, for which established statistical concepts, definitions and standards do not yet exist. In these circumstances, decision makers may need to rely on experimental data, models or alternative data sources.

One approach has been to compile datasets from non-traditional data, variously described as experimental or analytical. In Ireland, the CSO produces more than 60 *Frontier Outputs*¹, that range from *Port Visits Using Real-Time Shipping Data* to *How Dark is your Sky? Estimating Artificial Light in Ireland from Satellite Imagery*. At the OECD, several analytical databases use new data sources to dramatically improve timeliness and coherence. For instance, OECD data products exploiting Automatic Identification System vessel tracking signals and geospatial information provide rapid information on maritime trade dynamics and on shipping carbon dioxide (CO₂)

¹ <https://www.cso.ie/en/statistics/a-zofreleasespublications/csfrontieroutputs/#d.en.262925>

emissions, but depend on coverage quality and modelling assumptions that may bias results for certain routes, ports or vessel types (De Queljoe et al., 2025; Pilgrim et al., 2026). OECD estimates of CO₂ emissions from air transport, based on high-frequency flight activity data, also offer consistent global coverage yet remain sensitive to methodological choices about allocation and system boundaries (Clarke et al., 2022).

Beyond analytical databases, computational models are often relied upon to fill data gaps: nowcasting to improve timeliness, or forecasting to extend the analytical time horizon. For crisis response, and more broadly to support urgent policy needs, some reliance on models is usually unavoidable. This raises the uncomfortable issue of reliability. As Mervyn King, former Governor of the Bank of England, noted ‘Making forecasts is inherently difficult. They always turn out to be wrong’ (King, 2016, p. 180). The question is, how wrong? Are the nowcasted or forecasted estimates close enough to be useful, or so wide of the mark as to be misleading? Hence Box’s famous observation that ‘all models are wrong, but some are useful’ (Box, 1976). Often, one does not discover the utility of a model until a moment of crisis or stress. Then they either prove useful, or the wheels fall off.

The use of models brings two issues to the fore: dealing with and accepting uncertainty, and reliance on unofficial data. Our economies, our societies and the environment are messy and complex, and they rarely behave as we might wish, or as our models assume. This makes the transition from statistical analyses to policy formation inherently difficult. As Karabell (2014, p. 150) asserts, ‘The need to present policy and justify it using indicators forces a level of certainty and simplicity that flies in the face of that complexity’. Every dataset comprises value judgements and imperfections, which combined with modelling assumptions make uncertainty unavoidable. The crucial task is therefore to present uncertainty clearly, so that users understand and are confronted with the fact that they are not dealing with a definitive point estimate but a range. The difficulty is that communicating policy decisions with confidence seems to require either absolute certainty in the evidence, or the much rarer capacity to master both the evidence itself and the uncertainty surrounding it.

The second noteworthy issue is that models typically rely on unofficial data. Models are data hungry, and official statistics alone cannot usually satisfy their appetite. In practice, this pushes analysts towards alternative – often administrative or privately held – data

created for other purposes and only later repurposed for statistical ends. For example, the United Nations Conference on Trade and Development (UNCTAD) trade nowcast, which was publishing second quarter (Q2) 2026 estimates as early as May 2026, draws on a wide range of inputs, including official trade statistics, but also sentiment indicators, shipping and port statistics, manufacturing and production data, and so forth (UNCTAD, 2026). Reliance on such data may change the risk profile of the evidence base: coverage can be uneven, biased and results can be sensitive to vendor-imposed conditions and methodological choices that are not always transparent to the end user.

This dynamic is visible in high-frequency consumer spending indicators. Card payment transactions can be used to estimate retail activity just days after the reference period, often tracking the official series reasonably well, but they are conceptually narrower as they only capture card-based spending rather than total retail turnover. Such data can therefore be invaluable for speed – especially during shocks – but their coverage, behavioural shifts (cash-to-card), and provider-specific omissions can all affect representativity and stability over time. For policymakers, the implication is relatively straightforward: models can provide indispensable speed in a crisis, but the evidence must be accompanied by clear documentation on data provenance and methodology; otherwise, timeliness may be purchased at the cost of credibility and accountability.

As noted above, events happen, and some decision-making is necessarily geared towards anticipating and averting disaster. One data-based response to this challenge is to develop a dashboard. Dashboards, like every other tool, have their uses, but they also have an important blind spot: they can only provide signals for the indicators they are designed to track. There is a saying among soldiers that generals always fight the last battle. In relying too heavily on dashboards for surveillance, the same risk presents. Crises, like economies and societies, tend to evolve and mutate. Dashboards may help us to monitor the last pandemic, the last financial crisis or the last national emergency, but they may do little to warn us about what comes next unless the future resembles the past very closely. We can never know what the next emergency will be, but we can be fairly confident it will not be what we expect.

Statistics play a dual role: they not only measure reality, they also shape and define it. A dashboard monitors only the indicators included within it and therefore only the reality those indicators

define. While dashboards may help to warn us against known risks, they may blind us to unknown ones, thereby fostering a false sense of security. In most cases, therefore, foresight will not be improved by developing a dashboard. There is no short cut or silver bullet for analytical creativity and capacity. Ferguson (2022, pp. 399 and 412) captures the point well, arguing that ‘because we cannot predict disasters, it is better to be generally paranoid than it is to be bureaucratically prepared for the wrong contingency...we must try and cultivate [a] kind of general paranoia’.

Pressures and challenges in producing official statistics

The challenges facing official statistics are not entirely new, but they are becoming more acute. Statistical systems must now contend simultaneously with technological change, rising expectations for timeliness and granularity, growing concerns over privacy and trust, and a more fragmented and contested information environment. The task is not only to produce more and better data, but to safeguard quality, impartiality and credibility, while remaining relevant and serving the public good.

One challenge concerns data access. Modern statistical systems increasingly depend not only on traditional surveys and administrative records, but also on privately held data, including from major technology companies, and other non-traditional sources. Yet access to such data is often constrained by financial, legal, technical, commercial and institutional hurdles. There are already autumnal signs of what has been described as a ‘data winter’ (Verhulst, 2024), where data that were once publicly available are becoming harder to access and increasingly withheld for commercial or political purposes. In this increasingly contested informational marketplace, sustained access to critical data sources is becoming existential for the continued relevance of official statistics. In its 2021–2026 strategy, the NSB in Ireland highlighted the existential importance of Big Data for compiling official statistics and stressed the need to access private data sources for statistical purposes (NSB, 2021). It is noteworthy that one of the main reasons that European statistical legislation 223/2009 was updated in 2024 (European Commission, 2024) was to secure access to private data sources. It is also notable that in 2014, MacFeely and Dunne (2026) warned in the context of the Croke Park and Haddington Road agreements (Department of Public Expenditure and Reform, 2010; Labour Relations Commission, 2013), that in the

drive to modernise and privatise programmes that the ownership of public-sector data is retained by the state.

A second challenge concerns the social contract on which official statistics depend. Statistical systems rely on public trust and willingness to provide information, whether directly through surveys or indirectly through administrative and other records. As public trust erodes and willingness to provide information declines, survey response rates fall. For example, between Q4 of 2019 and Q4 of 2025, the response rate to the Labour Force Survey fell from 45 to 40 per cent in Ireland (CSO, 2019, 2025). This pattern is not unique to Ireland and has been observed elsewhere around the world (Nakkan, 2025; Johnson et al., 2026). Greater public sensitivity to privacy and broader skepticism – sometimes even disdain – towards institutions are straining the relationship between statistics offices and citizens. In this environment, trust can no longer be treated as given. It must be built, maintained, and rebuilt through professional independence, transparency, quality assurance and clear communication on how statistics are compiled, used and protected.

Artificial intelligence may exacerbate these tensions. At its best, AI can enhance statistical production, strengthen quality assurance, support analytical investigation, and improve user navigation. But it also raises risks for transparency, traceability, confidentiality and accountability (MacFeely, 2026). Thus, the use of AI in the production and interpretation of official statistics, and indeed in policy formation, should be carefully considered. The UNECE High-Level Group for the Modernisation of Official Statistics work on generative AI in official statistics has rightly stressed that the issue is not simply whether AI can be used in official statistics, but whether it can be governed in ways that protect quality, transparency and the social contract between statistical systems and the public (UNECE, 2025). The challenge, therefore, is not only technical but ethical and institutional.

Communication is another important issue. In a crowded information environment, official statistics compete with a diverse range of other statistical and data products. These range from potentially high-quality products – but often unaccompanied by metadata or methodological notes – to anecdote, emotion and deception. Mis- and dis-information are not merely external irritants; they can weaken the deliberative public space where evidence is used, interpreted and debated, threatening to undermine the longstanding connection between evidence and policy-making. Tasks once regarded

by many as peripheral – fostering statistical literacy, communicating uncertainty and proactive public communication – are now central. It is no longer enough to simply provide access to high-quality data to inform public debate.

Despite these challenges, there is cause for optimism. More official statistics are available today than ever before, with greater disaggregation and improved timeliness. Their dissemination has improved dramatically, with modern access and download tools, including application programming interfaces. Furthermore, new data sources, new methods and new technologies are making it possible to answer questions that would have once been out of reach. Evolving statistical laws, codes of practice, quality assurance frameworks and international standards now provide stronger protections for professional independence and clearer frameworks for access and accountability than existed in earlier eras of statistics. Initiatives to improve data governance are underway across statistical systems, working to improve microdata management, data exchange protocols and machine-readable metadata. However, as datasets grow larger and more powerful, and as speed and automation increase, evidence can shift from a supporting act to the leading role. Against this backdrop, the apparent rhetorical shift from ‘evidence-informed’ to ‘data-driven’ decision making warrants closer scrutiny.

Evidence-informed versus data-driven

At first glance, this evolution from ‘evidence-informed’ to ‘data-driven’ decision-making seems welcome – decisions are now driven by data, implying those decisions must be objective and scientific. Across international organisations, such as the United Nations, the OECD and others, reports prior to 2020 consistently referred to either evidence-based or evidence-informed decision-making. More recent reports increasingly refer to data-driven decision-making. This transition is evident in Irish policy documents too. For example, in the *Our Public Service 2020*, Ireland’s public service reform plan, there is a reference to an ‘evidence and data driven approach’ (Government of Ireland, 2017, p. 7). It rings of progress and modernity. But is this the case?

Evidence-informed decision-making acknowledges and makes transparent the judgements and trade-offs involved in democratic decision-making. Data-driven decision-making, however, can be interpreted in several ways. Do data drive policy debate, with the

eventual decision being ‘data-triggered’? Or do data, in and of themselves, take the decision, the eventual decision being ‘data-determined’? Recent rhetoric seems increasingly to indicate the latter, with decision-making resulting from a more technocratic, or datacratic approach, suggesting that data alone are sufficient to make decisions once guiding parameters have been set. It is, in today’s parlance, an algorithmic approach (MacFeely & Ward, 2025).

It is not always clear how such decisions are made, how they accommodate unusual circumstances, or what input data were used. In short, there are issues concerning transparency. As decision-making is automated, the process may slip into the shadows, hidden from view, so much so that customers, the public or citizens may not even be aware of the decisions being made.

This is concerning because, as noted above, algorithms or what Tufekci has called ‘semi-savant mini-Frankensteins’ (quoted in Tenner, 2018) may perpetuate, reinforce and amplify, often unconscious, biases and stereotypes. These biases, especially in a data-determined algorithmic world really matter, as they may hard-code discriminatory decisions into public administrations and private-sector organisations, without any transparency or recourse (e.g. whether you are successful in securing a social protection benefit or affordable health insurance).

Principle 1 of the United Nations Fundamental Principles of Official Statistics (United Nations General Assembly, 2014) states that official statistics provide an indispensable element in the information system of a democratic society. The OECD Recommendation of the Council on Good Statistical Practice (OECD, 2019) too considers that quality statistics are an indispensable tool for good analysis, transparency, accountability and for informed decision-making and the functioning of democracies. These statements rest on the ideal that statistics should be the neutral arbiters in political debate and are an essential pillar in any deliberative public space.

In a democracy, citizens elect leaders, entrusting them to make important decisions on their behalf. Official statistics are one important tool in the armoury of those elected decision makers, providing an objective benchmark to ground political debate and assess alternatives. A data-driven world or a data-determined one, threatens to remove a fundamental step from that democratic process, by removing the decision maker from the decision. Pilling (2018, p. 237) notes the fallacy of ‘the idea that government interventions can be cleansed of any moral or ideological principles, and be guided

purely by facts and figures'. Algorithms, like any computationally reducible model are just simplifications of reality, and will obey programmatic codes, not codes of ethics. They are manmade and are not immune from poor or biased choices. Official Statistics are produced to inform decisions, not to make them – they are produced to support democracy, not to replace it.

Conclusion

Official statistics are, and should remain, a cornerstone of evidence-informed policy-making because they provide professionally independent, quality-assured, and transparent evidence to guide decisions and evaluate outcomes. Their purpose is not to drive or determine decisions, but to support democratic judgement. At their best, they offer a climbing frame: helping policymakers rise above the noise, assess alternative options, and make better choices. They should not be allowed to become a cage that limits options, or a crutch lent on too heavily to justify decisions. As Muller (2018, p. 204) warns, overreliance on empirics is an 'abdication of responsibility and signals a loss of will and courage to defend ideas'.

While Ireland has an ambitious statistical development programme for the years ahead (CSO, 2026), it already enjoys one of the strongest statistical systems in the world. The CSO and the wider ISS provide a wide range of statistical products that adhere to international norms and standards. Ireland has a robust national statistical law and code of practice, supported by strong European Union legislation and codes of practice. The ISS is grappling with all the challenges and trade-offs discussed in this paper, but throughout its history it has proven to be a resilient system that continues to innovate and produce high-quality, trustworthy and impartial statistics that inform pressing policy decisions (NSB, 2025). This strength should not be taken for granted. Events around the world – including the falsification of government deficit and debt statistics in Greece (Mink, 2022; Eurostat, 2024), problems with the Labour Force Survey and the suspension of a number of accredited official statistics in the United Kingdom (Stuart, 2024; Office for Statistics Regulation, 2026), and most recently the widespread deterioration of availability and quality of public statistics in the United States of America (American Statistical Association, 2025) – illustrate that navigating a safe path through fiscal and political cycles is not always straightforward. In addition to the CSO and the NSB, the Irish Government Economic and Evaluation Service,

established in 2012, and the more recently established Civil Service Research Network have an important role to play in supporting the ISS and ensuring the continued use of official statistics to inform public policy in Ireland.

In this era of quantification, slogans such as ‘what cannot be measured cannot be managed’ are too often treated as self-evident truths, when they are nothing of the sort. Statistics are necessarily reductionist: that is their purpose and often their strength. They distil the complexities of life into measures that can guide judgement. But once an indicator is elevated to a target, it may lose its value as an indicator – a point well-captured by Goodhart’s law, which reminds us that when a measure becomes a target, it ceases to be a good measure. And because aggregates can conceal as much as they reveal, analysts must look beyond the headline figure to underlying distributions. The danger, then, is not measurement itself, but what Muller (2018) has called ‘Obsessive Measurement Disorder’ – the belief that counting more things will automatically produce better policy. Measures, like so many useful tools, are good servants but poor masters, and they must remain subordinate to context, analysis and judgement.

References

- Agar, J. (2001). *Turing and the universal machine – The making of the modern computer*. Icon Books Ltd.
- American Statistical Association. (2025). *The nation’s data at risk: 2025 report*. www.amstat.org/policy-and-advocacy/the-nations-data-at-risk—2025-report
- Bernstein, P. L. (1996). *Against the gods: The remarkable story of risk*. John Wiley & Sons.
- Boaz, A., Grayson, L., Levitt, R. & Solesbury, W. (2018). Does evidence-based policy work? Learning from the UK experience. *Evidence & Policy – A Journal of Research Debate and Practice*, 4(2), 233–53.
- Borgman, C. L. (2015). *Big Data, little data, no data scholarship in the networked world*. MIT Press.
- Box, G. E. P. (1976). Science and statistics. *JASA*, 71, 791–9.
- Central Statistics Office. (2013). *Irish Statistical System Code of Practice (ISSCoP)*. www.nationaldata.ie/Standards/ISSCoP/CodeofPractice/
- Central Statistics Office. (2016). *Report of the Economic Statistics Review Group (ESRG)*. [www.cso.ie/en/media/csoie/newsevents/documents/reportoftheeconomicstatisticsreviewgroup/Economic_Statistics_Review_\(ESRG\)_Report_Dec_2016.pdf](http://www.cso.ie/en/media/csoie/newsevents/documents/reportoftheeconomicstatisticsreviewgroup/Economic_Statistics_Review_(ESRG)_Report_Dec_2016.pdf)

- Central Statistics Office. (2019). *Labour force survey Q4-2019. Background notes*. www.cso.ie/en/releasesandpublications/er/lfs/labourforcesurvey/lfsquarter42019/
- Central Statistics Office. (2025). *Labour force survey Q4-2025. Background notes*. www.cso.ie/en/releasesandpublications/ep/p-lfs/labourforcesurveyquarter42025/backgroundnotes/
- Central Statistics Office. (2026). *CSO data strategy 2026–2028*. www.cso.ie/en/releasesandpublications/cp/cp-ds/csodatastrategy2026-2028/
- Clarke, D. et al. (2022). *CO₂ emissions from air transport: A near-real-time global database for policy analysis*. OECD Statistics Working Papers, No. 2022/04, OECD Publishing. <https://doi.org/10.1787/ecc9f16b-en>
- Davis, E. (2017). *Post truth: Peak bullshit and what we can do about it*. Abacus.
- Department of Public Expenditure and Reform. (2010). *Public service agreement 2010–2014*. www.gov.ie/en/office-of-public-works/publications/public-service-agreement-2010-2014-croke-park-agreement/
- Desrosières, A. (2010). Words and numbers: For a sociology of the statistical argument. In, A.R. Saetnan, H.M. Lomell and S. Hammer (eds), *The mutual construction of statistics and the society*. Taylor & Francis Group.
- De Queljoe, M. et al. (2025). Analysing recent trends and drivers of maritime transport CO₂ emissions: Insights from a decomposition analysis for the OECD and the world. *OECD Statistics Working Papers*, No. 2025/03, OECD Publishing. <https://doi.org/10.1787/6bb2bd69-en>
- European Commission. (2017). *European statistics code of practice*. <https://ec.europa.eu/eurostat/fr/web/products-catalogues/-/ks-02-18-142>
- European Commission. (2024). Regulation (EU) 2024/3018 of the European Parliament and of the Council of 27 November 2024 amending Regulation (EC) No 223/2009 on European statistics. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=OJ:L_202403018
- Eurostat. (2024). Report by Eurostat on the revision of the Greek Government deficit and debt figures. <https://ec.europa.eu/eurostat/web/products-eurostat-news/-/greece>
- Ferguson, N. (2022). *Doom*. Penguin Books.
- Fogel, R., Fogel, E. M., Guglielmo, M. & Grotte, N. (2013). *Political arithmetic: Simon Kuznets and the empirical tradition in economics*. University of Chicago Press.
- Fukuda-Parr, S. & McNeill, D. (2019). Knowledge and politics in setting and measuring the SDGs: Introduction to special issue. *Global Policy*, 10(1), 5–15.
- Gitelman, L. (Ed.). (2013). *‘Raw data’ is an oxymoron*. MIT Press.
- Government of Ireland. (2017). *Our Public Service 2020 – Development and Innovation, December 2017*. <https://assets.gov.ie/static/documents/our->

- public-service-public-service-reform-plan-2020.pdf
- Johnson, D. S., Meinhardt, M. & Sabelhaus, J. (2026). Why did people stop responding to federal economic surveys? What can be done? *Brookings Commentary*. www.brookings.edu/articles/why-did-people-stop-responding-to-federal-economic-surveys-what-can-be-done/
- Karabell, Z. (2014). *The leading indicators – A short history of the numbers that rule our world*. Simon and Schuster.
- King, M. (2016). *The end of alchemy – Money, banking and the future of the global economy*. Little, Brown Book Group.
- Labour Relations Commission. (2013). *Public service stability agreement 2013–2016: The Haddington Road agreement*. <https://assets.gov.ie/static/documents/haddington-road-agreement.pdf>
- Livera, J. (2025). *Beyond the hype: Why generative AI can't be the final word on data accuracy*. Finn Partners. www.finnpartners.com/news-insights/beyond-the-hype-why-generative-ai-cant-be-the-final-word-on-data-accuracy/#:%E2%88%BC:text=AI%20Accuracy%3A%20Generative%20AI%20often,miss%20critical%20nuances%20in%20research
- Luce, E. (2017). *The retreat of Western liberalism*. Little, Brown Books.
- MacFeely, S. (2020). In search of the data revolution: Has the official statistics paradigm shifted? *Statistical Journal of the IAOS*, 36, 1075–94.
- MacFeely, S. (2026). The role of AI in Official Statistics: Black hole or worm hole? *Statistical Journal of the IAOS*, 42(1), 218–24.
- MacFeely, S. & Barnat, N. (2017). Statistical capacity building for sustainable development: Developing the fundamental pillars necessary for modern national statistical systems. *Statistical Journal of the IAOS*, 33(4), 895–909.
- MacFeely, S. & Dunne, J. (2026). Joining up public service information: The rationale for a national data infrastructure. *Administration*, 74(1), 133–49. <https://doi.org/10.2478/admin-2026-0009>
- MacFeely, S. & Nastav, B. (2019). You say you want a [data] revolution: A proposal to use unofficial statistics for the SDG Global Indicator Framework. *Statistical Journal of the IAOS*, 35, 309–27.
- MacFeely, S. & Ward, A. (2025, 7 May). From evidence-informed to data-driven. *OECD Statistics Blog*. <https://oecdstatistics.blog/2025/05/07/from-evidence-informed-to-data-driven/>
- Mahajan, M. (2019). The IHME in the shifting landscape of global health metrics. *Global Policy*, 10(1), 110–20.
- Marawala, T. (2024). Never assume that the accuracy of artificial intelligence information equals the truth, UN University. <https://unu.edu/article/never-assume-accuracy-artificial-intelligence-information-equals-truth>
- Masood, E. (2016). *The great invention: The story of GDP and the making and unmaking of the modern world*. Pegasus Books Ltd.

- Mink, R. (2022). *Official statistics – A plaything of politics?* Springer Nature.
- Morgan, O. (2025). *The curious case of “Machine Bullshit”*. Artificial Public Health Intelligence. <https://aipublichealth.substack.com/p/the-curious-case-of-machine-bullshit>
- Muller, J. Z. (2018). *The tyranny of metrics*. Princeton University Press.
- Nakkan, C. (2025). *Statistics in shambles: The crisis at the Office for National Statistics*. Intergenerational Foundation.
www.if.org.uk/2025/09/18/statistics-in-shambles-the-crisis-at-the-office-for-national-statistics/
- National Statistics Board. (2003). *Strategy for statistics 2003–2008*.
www.nsb.ie/media/nsbie/pdffdocs/StrategyforStatistics2003-2008.pdf
- National Statistics Board. (2021). *Quality information for all: Numbers matter. National Statistics Board strategic priorities for official statistics 2021–2026*.
www.nsb.ie/media/nsbie/pdffdocs/NSB_Statement_of_Strategy_2021_2026.pdf
- National Statistics Board. (2025). *Numbers matter –mid-term review. National Statistics Board strategic priorities for official statistics 2021–2026*.
www.nsb.ie/media/nsbie/pdffdocs/NSB_Statement_of_Strategy_Mid-term_Review_-_Jan_2025_-_ENG.pdf
- Office for Statistics Regulation. (2026). *The list of cancelled/suspended accreditations*. <https://osr.statisticsauthority.gov.uk/accredited-official-statistics/>
- Oireachtas. (1993). Statistics Act, 1993. Number 21 of 1993.
www.irishstatutebook.ie/eli/1993/act/21/enacted/en/html
- Organisation for Economic Co-operation and Development. (2016). *Are the Irish 26.3% better off?* www.oecd.org/en/data/insights/data-explainers/2016/10/irish-gdp-up-by-26-per-cent-in-2015.html
- Organisation for Economic Co-operation and Development. (2019). *Recommendation of the Council on Good Statistical Practice*.
<https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0417>
- PARIS21. (2005). *Models of statistical systems*. Document Series No. 6. 2005.
www.paris21.org/sites/default/files/2101.pdf
- PARIS21. (2025). *Data-driven policymaking? The politics, people and practices behind gender data use*.
www.paris21.org/sites/default/files/media/document/2025-10/gender-data-use.pdf
- Patinkin, D. (1976). Keynes and econometrics: On the interaction between the macroeconomic revolutions of the inter war period. *Econometrica*, 44(6), 1091–123.
- Pilgrim, G., Dorville, Y. & Mourougane, A. (2026). Monitoring global trade by products, using Big Data. *OECD Statistics Working Papers*, No. 2026/02. OECD Publishing. <https://doi.org/10.1787/e0447f00-en>
- Pilling, D. (2018). *The growth delusion. The wealth and well-being of nations*. Bloomsbury Academic.

- Rosling, H., Rosling, O. & Rosling-Ronnlund, A. (2018). *Factfulness: Ten reasons we're wrong about the world – and why things are better than you think*. Flatiron Books.
- Rostow, W. W. (1959). The stages of economic growth. *The Economic History Review*. Second Series, 12(1), 1–16. <https://doi.org/10.1111/j.1468-0289.1959.tb01829.x>
- Rudder, C. (2014). *Dataclysm: What our online lives tell us about our offline selves*. 4th Estate.
- Stuart, H. (2024, 3 December). ONS inability to fix labour force survey until 2027 'a major blow', MPs hear. *The Guardian*. www.theguardian.com/uk-news/2024/dec/03/ons-replace-labour-force-survey-uk-jobs-market
- Taylor, A. J. P. (1961). *The origins of the Second World War*. Simon and Schuster.
- Tenner, E. (2018). *The efficiency paradox: What Big Data can't do*. Alfred A. Knopf.
- United Nations Conference on Trade and Development. (2026). *Trade nowcast*. <https://unctadstat.unctad.org/EN/Nowcasts.html>
- United Nations Department of Economic and Social Affairs. (2025). *Handbook on management and organization of national statistical systems*. Version 2025/A. <https://projects.officialstatistics.org/hb-mgnt-org-nss/handbook/intro.html>
- United Nations Economic Commission for Europe. (2025). *Generative AI for official statistics. HLG-MOS report*. <https://unece.org/statistics/documents/2025/09/reports/generative-ai-official-statistics-hlg-mos-report>
- United Nations General Assembly. (2014). *Fundamental principles of official statistics*. A/RES/68/261. <https://unstats.un.org/unsd/dnss/gp/FP-New-E.pdf>
- Verhulst, S. G. (2024). Are we entering a “Data Winter”? *Medium*, 23 January. <https://sverhulst.medium.com/are-we-entering-a-data-winter-f654eb8e8663>