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MONITORING SYSTEMS IN AFRICA

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10.52779/9781991260154/07

C.B. Mapitsa & C. Churchill (eds.). Monitoring Systems in Africa. Stellenbosch: African Sun Media

Chapter 7: Monitoring in an Era of Algorithmic Governance

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Introduction

In a world that has become more connected, interdependent, and data-rich, and where Internet users tripled from 1 billion in 2005 to 3.2 billion in 2015, digital services have increasingly allowed new actors to become producers, owners, and consumers of data (Bamberger 2016:29). The rapid increase in data and information across the various aspects of our society has altered the logic and way institutions and organisations operate internally and externally. However, as argued by York and Bamberger (2020), the current usages of big data and data analytics have focused on areas of implementation, coordination, the management of programmes, strategies, and services but has not found wide scale usage with regards to the monitoring and evaluation (M&E) of these efforts and programmes. For instance, the administrative data produced by public institutions alone, if mined appropriately, provides a plethora of opportunities to better understand "societal patterns, trends and policy impacts" and, if sanitised and released to the broader public, could fuel the innovation of products and services unbeknownst to these institutions themselves (Veale and Brass 2019:2).

Our point of departure is 'datafication' (Mayer-Schönberger and Cukier 2013), which refers to "the ability to transform non-traditional information sources such as text, images, and transactional records into data" (Diermeier 2015). Datafication has "created the opportunity for policymakers to have deeper, data-driven insights" (Nuamnovic 2017) and "allowed quantitative analysis to penetrate the policy process more deeply than ever before" (Diermeier 2015). As a result, as Denick et al. (2019:3) argue that it has become increasingly important to understand the technical ability to convert "increasing amounts of social activity and human behaviour into data that can be collected and analysed". This, in turn, demands an investigation of the relationship between M&E specialists and data scientists.

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The use of data, particularly within the public sector, is established and has been of central concern for the M&E of government activities. Performance measurement places a central focus on the relationship between inputs, outputs, outcomes, benchmarks, citizen satisfaction, productivity, and the tools available to observe the data generated by these distinct but interdependent entities, and whether they achieve the public objectives (Williams 2003:643).

It also poses the question of the role of data science in understanding various public administration processes concerning the evolving nature of public governance caused by increased datafication and digitalisation. The reforms within this sector are driven by digital service transformations such as Industry 4.0 (I4.0), 'e-government 3.0', and the creation of integrated data infrastructures within the state, which were designed to improve the experience of citizens by making governments more efficient (Veale and Brass 2019:2). To achieve this, there is also a need to look into the operations and systems within government and the role that datafication and digitalisation play in the transformation of these structures.

A further need is to understand the potential impact that algorithmic governance will have on monitoring systems within the state. 'Algorithmic governance' here refers to a form of government of social ordering, where the usage of algorithms (especially artificial intelligence) is applied to public policy development and implementation. It does not refer to the governance of algorithms.

Considering these changes, what remain certain for evaluators and data scientists are three uses of data for policy maintenance and generation: i) that data and evidence should be used to effectively inform decisions on appropriate policy action; ii) data generated from the evaluation of policies should be used to inform decisions regarding whether to continue, halt, or improve policies; and iii) that evidence is used to inform the future consideration of policy options (Sanderson 2002:4).

A central concern for the use of data within the public sector, and monitoring systems in Africa in particular, is institutional readiness. This concern is in relation to institutional systems, cultures, and methodological approaches that are not in full alignment with approaches endorsed by data scientists. The barriers to the institutional preparedness of monitoring systems related to datafication in the public sector include the cost of data collection, the lack of IT infrastructure, and in other cases, the presence of various risks associated with legacy IT systems within the state. Other barriers include the lack of skilled data practitioners who can use data and understand the value of data generation, and the lack of governance frameworks focused on the management of data for the 21st century. This chapter works towards understanding these challenges as opportunities for both monitoring systems and data evaluators.

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This chapter is premised on two assumptions about the public sector in Africa. The first is that it is highly politicised, meaning that politics influences decisions deep within civil service. There is nothing uniquely African about that. In the United States, the president and the cabinet secretaries can appoint over 4 000 employees, and countries previously thought to be immune to politicisation (e.g., Denmark and New Zealand) have succumbed to "creeping politicisation" (Halligan 2021:2). However, politicisation — political appointments throughout the civil service, partisanship in promotions, the use of ministerial advisors, the reliance on ministerial cabinets, etc. — is a common feature throughout the African continent, and something all African public servants must take into consideration.

The second assumption is that the African public sector suffers resource constraints with regards to finance and in terms of human resources. With low tax-to-GDP ratios, African governments have little fiscal space to attract and retain talent and invest in digitalisation and data collection. In 2019, the tax-to-GDP ratio in Africa was only 16.6%, according to a report by the Organisation for Economic Development and Cooperation, the African Union Commission, and the African Tax Administration Forum (2021). By comparison, it was 22.9% in Latin America and the Caribbean, and 33.8% among OECD countries.

The chapter is structured as follows: Section 1 discusses the drivers of datafication and their implication on data analytics. Section 2 details how datafication has impacted both M&E specialists and data scientists. Section 3 examines the methodological differences between the approaches to monitoring between M&E specialists and data scientists. Section 4 details how monitoring has changed as governance systems have evolved, culminating with the emergence of algorithmic governance[23] and the broad challenges it has created. Section 5 highlights the democratic and technocratic implications of algorithmic governance for both evaluators and data scientists.

Drivers of Datafication

The argument in this chapter is based on three observations. The first is that data volumes are increasing. Figure 1 plots the change in global data volumes from 2010 to 2025. It suggests that by 2025 global data volumes will reach 181 zettabytes, up from 64.2 zettabytes in 2020.[24] Since 2010, data volumes have doubled every two to three years. This means around one-fourth of the data ever produced was produced last year, while 80% was produced over the course of the last five years. Nothing suggests that the trend is about to reverse. According to the International

23 'Algorithmic governance' here refers to a form of government of social ordering, where the usage of algorithms, especially artificial intelligence, is applied to public policy development and implementation. It does not refer to the governance of algorithms.

24 One zettabyte is 10^{21} (10 followed by 21 zeros) bytes: approximately the amount of data that can be stored in 250 billion DVDs.

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Telecommunication Union, 63% of the world's population is now online (2021). Every day, they send 300 billion emails (Lynkova 2021), 100 billion WhatsApp messages (Singh 2020), and 8 billion messages on Facebook (Bulao 2021). They post more than 500 million stories on Instagram (Chernev 2021) and upload 720,000 hours of videos on YouTube (Petrov 2021). An estimated 46 billion Internet of Things (IoT) devices also contribute to the increasing data volumes (Galov 2021). For example, the 770 million surveillance cameras currently installed produce more than nine quadrillion images every day (Bischoff 2021), assuming an average frame rate of 15 frames per second.

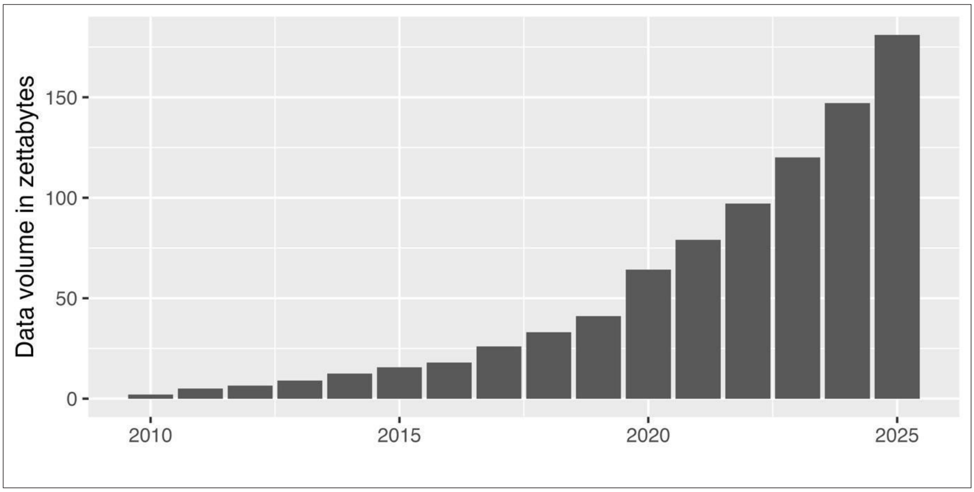

Figure 7.1: Reinsel et al., *Global Data Volumes*, 2010 - 2015

While a lot of data is produced, a lot less is stored. Rydning and Reinsel (2021) estimate that global storage capacity will only reach 16 zettabytes by 2025, which means that 90% of the data produced will be lost. Data is generally stored in three locations. The first is called endpoints, which are the personal computers, mobile phones, IoT devices, etc., that produce most of the data. The second location is the edge, including mobile phone towers, institutional servers, and smaller data centres set up to reduce response times and meet privacy requirements. The third and final location is the core, which includes traditional servers and cloud-computing data centres. There are around 600 hyperscale data centres (centres with more than 5 000 servers) in the world. The two largest are the China Telecom Data Centre in Hohhot, China, which occupies one square kilometre, and The Citadel in Tahoe Reno, the United States, which occupies 700 000 square metres and uses 815 megawatts of power. To meet the growing demand for storage capacity, around 50 hyperscale data centres are built every year.

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The second observation made in this chapter is that the nature of data is changing. Data scientists make a distinction between 'structured' and 'unstructured' data. Structured data refers to data that is neatly organised in rows and columns, such as an Excel spreadsheet detailing information from a survey. Each row typically represents a respondent, while each column captures information about that respondent: gender, age, level of education, employment status, income, etc. The spreadsheet may miss information or contain empty cells, but it does not fundamentally alter the structure of the data. Unstructured data, by contrast, is unorganised. Rather, it is not organised in any predefined manner. Examples of this are text, images, videos, sound, etc. Reinsel et al. (2021) predicts that 80% of global data volumes will be unstructured by 2025.

A lot of the unstructured data is 'data exhaust', which is what the trail of data we leave behind when we browse the Internet is called. Every click, scroll, or hovering of a cursor produces data stored in the form of cookies, temporary files, logfiles, storable choices, etc. The data is captured to improve individual online experiences through the customisation of content. However, it can also be used to generate knowledge. Google, for example, uses data exhaust to optimise the placement of advertisements (Zuboff 2015). A company's advertising services are offered under a pay-per-click pricing model, which results in advertisers exclusively paying under the condition of a Google user clicking on their advertisement. To maximise profits, Google uses cookies and keywords determined by advertisers to match advertisements with Google users who may be interested and are more likely to divert their browsing. This matching of advertisements and Google users is at the core of Google's business model. In 2020, Google Ads, the company's advertising platform, was the main source of revenue for Alphabet Inc., Google's parent company, contributing USD 168.6 billion (Alphabet Inc. 2021).

The changing nature of data also means the boundary between research methods is becoming increasingly blurred. Scientists make a fundamental distinction between quantitative and qualitative data, where the former refer to numeric data, while the latter refers to non-numeric data. The distinction has shaped our thinking around data and research methods. Most social science degrees and programmes, for example, separate their quantitative and qualitative methods training, and many social scientists identify as either quantitative or qualitative researchers. The distinction has also contributed to the 'paradigm war' (Gage 1989). This was originally a debate between different ontological and epistemological positions in many fields, and it developed into a debate over the merits and assumptions of different research methods (Bryman 2008). However, recent advancements in data science are beginning to erase the boundary between the two methods. All types of data – whether numeric or non-numeric – can now be processed through the use of a computer.

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Text is perhaps the most typical example of qualitative data, and documents, transcripts, field notes, etc. are important sources of information for qualitative researchers. However, text can also be converted into numbers. This is done in social media post analysis processes. In theory, social media posts are qualitative or non-numeric data. However, since they are published online, in practice, they are not. Text mining is an AI technology that uses natural language processing (NLP) to transform unstructured text into structured data, suitable for analysis or to drive machine learning (ML) algorithms. It can identify facts, relationships, and patterns that would otherwise remain hidden for the qualitative researcher, buried in the mass of textual big data.

Our third and final observation is that processing power is improving. In 1975, Gordon Moore, the co-founder of Intel, one of the world's largest semiconductor manufacturers, predicted that the number of transistors in an integrated circuit would double every two years. Moore's prediction, which has since become known as Moore's Law, has largely proven true. Figure 2 plots the number of transistors in an integrated circuit from 1971 to 2017. In 1971, this number was 2 308. By 2017, it had increased to 19.2 billion, giving an annual growth rate of around 42%: just short of Moor's prediction.

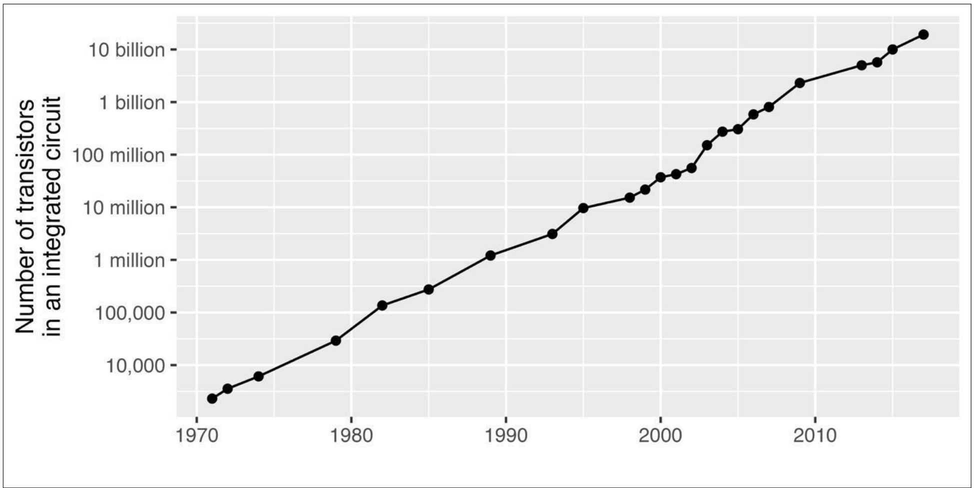

Figure 7.2: Rupp, *Transistors in an integrated circuit*, 2018

The importance of the number of transistors in an integrated circuit or a microprocessor is due to it being the determining factor in the processing power of a computer. Transistors in a microprocessor can be compared to cylinders in a car engine: the more cylinders, the more horsepower, the faster the car drives. Similarly, the more transistors in a microprocessor, the more processing power, and the faster a computer can execute commands.

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Moore's Law has pushed the boundaries of data science and enabled us to work with larger datasets and techniques that previously took days or weeks to implement or existed only in theory. Machine learning (ML) can be taken as an example of this. In 1959, when Arthur Samuel developed his checkers-playing programme (Samuel 1959), which was the first successful implementation of ML, he used an IBM 704: a computer the size of 15-20 large refrigerators, which could execute around 40 000 commands per second. Today, far more complex algorithms can be run even on ordinary laptops, and ML has become a standard tool for most data scientists. In fact, advances in ML are driving an entirely new type of 'autonomous analytics'. Historically, analytics were for decision-makers who were expected to consider the outputs and make decisions. With advancements in ML, computers can do this in their stead. This means that corrective action can be taken much faster, an example being instances of policies having unexpected negative spillover effects. However, it also raises questions of accountability. This is further discussed below.

Bringing M&E Specialists and Data Scientists Closer Together

Monitoring activities exist within an interventionist culture that focuses on evidence-informed decision-making. As Head (2008:2) explains, the state's use of evidence is ideally linked to its aspiration to produce knowledge that would be required for the "fine-tuning of programs and constructing guidelines and 'tool-kits' for dealing with known problems". However, various challenges persist regarding the integration of M&E specialists and data scientists relating to differences in institutional cultures and methodological approaches. These differences explain how M&E specialists and data scientists utilise different research and management paradigms consisting of different terminologies and approaches to similar questions, i.e. how to monitor interventions, the nature, quality, and utility of various types of data, and the role of theory informing data usage (Bamberger 2016).

An analytical framework devised by Langer and Weyrauch (2020) provides a valuable tool to understand the culture that M&E specialists find themselves situated within. For Langer and Weyrauch, three factors are important. The first is the demand for evidence within the state which relates to the generation, use thereof, and change mechanisms related to evidence. The second relates to the external context that informs the relationship between the state, its macro-political context of evaluation, and its various stakeholders. Lastly, the internal context of a state's M&E processes is influenced by culture, organisational capacity, management, and resources at the state's disposal (Langer and Weyrauch 2020). The changes in governance due to datafication will inevitably alter how M&E specialists engage with all three factors.

To further augment this framework, the nature of knowledge that M&E specialists must consider is also of importance. Head (2008) provides a useful intervention noting that evidence-informed decisions must contend with the political, scientific,

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and practical implementation of knowledge. The policy relates to the external political constraints, the limits of data, and the nature of interventions employed (Head 2008). Scientific implementation of monitoring and evaluation relates to the chosen methodologies used by M&E specialists to gather and analyse information. Two broad fields inform the methodological use of data: obtaining methodological rigour through experimentation with data for evidence-informed decision-making, or a more hermeneutic approach that emphasises iterative learning based on research projects (Head 2008). The practical implementation of knowledge refers to the ability for evaluators to understand the internal institutional challenges to the implementation of programmes that require a level of management that is upwards, downwards, and outwards with internal stakeholders (Head 2008).

The developments within the field of data science have created a variety of challenges relating to the external context that monitoring services that exist within the state, the practical utilisation of data for monitoring, and the actual strategies of using data that confront traditional means of monitoring the public sector. Figure 3 illustrates how both frameworks are combined to provide a means to compare both M&E specialists and data scientists within the context of increased datafication. Table 1 compares how the framework relates to both M&E specialists and data scientists. We use the framework to provide a means of comparing how datafication impacts both M&E specialists and data scientists within monitoring systems created by the state.

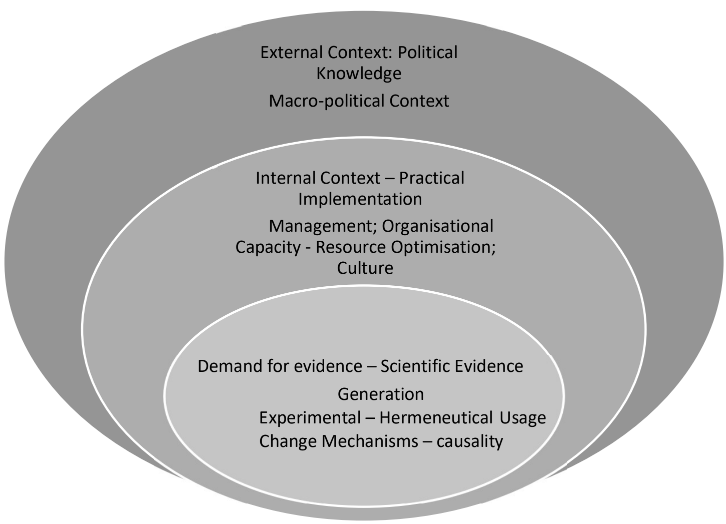

Figure 7.3: Head and Weyrauch, *Framework combination and comparison*, 2008 and 2020

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Table 7.1: M&E Specialists and data scientists

	Evaluators	Data Scientists
External Context: Political Knowledge	Macro-Context Intra-relationships with stakeholders and non-state agents	Politics of Data generation and usage Privacy Surveillance Legal and regulatory requirements
Internal Context: Practical Implementation	Culture Organisational Capacity Management Resource Optimisation Individual/Organisational/Systems Change Motivation to use evidence Capability to use evidence Opportunity to use evidence	Data Governance Governance Mechanisms Structural Mechanisms Procedural Mechanisms Relational Mechanisms
Demand for Data – Scientific Data usage	Evidence Generation Use Intervention Change Mechanisms	Data Scope Domain Scope

How Datafication Augments M&E at the External Level

The drivers of change that inform the evolving nature of data and governance have various implications for traditional M&E specialists and data scientists within the public sector. Both must contend with external political constraints placed on their activities. As seen in Table 1 and Figure 3, the external cultural context described by Langer and Weyrauch relates to Head's considerations of the political constraints placed on the use of data. While M&E specialists focus on the broader political context of M&E and its uses by the state, data scientists within the public sector must contend with the increasing political suspicion regarding the use of data by public institutions. Datafication and its various usages has created a need for new legal and regulatory requirements for both M&E specialists and data scientists.

Increased levels of data generation by both the private sector and the state have resulted in a resurgence of interest by citizens, businesses, and non-state actors on issues such as privacy, surveillance, anonymity, and digital discrimination. This increased scrutiny has led to an increase in guidelines, regulations, and legislation related to data protection and the rights allocated to data users and generators (Ruppert et al. 2017), all of which inform the strategies undertaken by M&E specialists

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and data scientists. The politicisation of data is less about data itself, but rather the political constraints placed on the use of data and its generation (Ruppert et al. 2017).

The outcome of this renewed interest in governments' use of data to inform policy decisions results in the belief that individuals need to protect themselves from ensuing politics related to data generation. The cause of this is varied, though according to Hilden (2019), it results from the increased marketisation of personal information continuously generated by individuals. Though data remains value-neutral, data itself provides varying levels of economic value to various actors in society. Increased marketisation of personal information results from the understanding that "data on individuals and their performance generates greater efficiency and control" over social behaviours that can be quantified, and individual behaviour can be predicted (Hildén 2019:29).

How Datafication Augments M&E at the Internal Level

The internal institutional context of evaluators is informed by practical limitations of using data. As seen in Table 1, for M&E specialists, these limitations relate to organisational capacity, resources, and the management of data amongst others. All of these inform the internal institutional context of monitoring, how data scientists must contend with the mechanisms related to the structure of data, the procedures related to its usage, and how data within an institution relates to its various functions. Improved computational possibilities have naturally created new management information systems that will inevitably be integrated into programme designs, management, monitoring activities, and evaluation studies (Ruppert et al. 2017:200; York and Bamberger 2020).

Data governance within the state becomes an essential consideration for any monitoring activity. The use of data analytics in the public service primarily seeks to categorise, segment, rate, and rank specific populations, administrative activities, and various transactional datasets. Once data is appropriately organised, the intent of data analytics and data governance becomes the efficient allocation of resources and services.

According to Abraham, Schneider, and Brocke (2019:425), based on a systematic review of literature of data governance, "data governance specifies a cross-functional framework for managing data as a strategic enterprise asset. In doing so, data governance specifies decision, rights, and accountabilities for an organisation's decision-making about its data. Furthermore, data governance formalises data policies, standards, and procedures, and monitors compliance".

Abraham et al. (2019) argues for an understanding of data governance through its relation to governance mechanisms that comprise formalised structures that connect the activities of the state with its IT capabilities and data management

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functions. This includes the "formal processes and procedures for decision-making and monitoring, and practices supporting the active participation of and collaboration among stakeholders" (Abraham et al. 2019:428). These mechanisms are structural, procedural, and relational. Structural mechanisms refer to reporting structures that indicate the roles and responsibilities of data and governance bodies that allocate decision-making authority regarding the use of data. Procedural and relational mechanisms refer to how "data is recorded accurately, held securely, used effectively, and shared appropriately", and the management of the collaboration of data amongst stakeholders (Abraham et al. 2019:429).

How Datafication Augments the Methodological Approaches to Monitoring

Datafication and advancements towards algorithmic governance will undoubtedly force M&E into a new realm where traditional approaches and techniques, though helpful, may not be the most efficient means of creating an understanding of public sector performance and impact. As an example, M&E specialists may soon be required to generate or synthesise new technologies based on existing data, including data exhaust, rather than collect new data (York and Bamberger 2020). Data scientists already have various tools at their disposal to account for this across the policy and programme cycle.

Rather than relying on the diagnostic, design, implementation, and outcome or impact cycle of policy development, data scientists view data that informs policy through the framing of descriptive and exploratory analysis, predictive analytics, detection, and evaluation or prescription (Bamberger 2016). The descriptive and exploratory analysis focuses on the compilation of large datasets that would ordinarily be beyond the capacity of conventional tools. For instance, the use of real-time data collection tools (for both structures and unstructured datasets) allows for the dynamic monitoring and generation of actionable data on project problems as well as new opportunities. Evaluators rely on more familiar tools such as surveys, project records, and official statistics (Bamberger 2016; York and Bamberger 2020:25). Furthermore, while evaluators may utilise theory-based approaches to evaluation design, the use of theory is less specific for data scientists (Bamberger 2016; Langer and Weyrauch 2020).

For M&E specialists, experimental or quasi-experimental research focuses on assessment of the causal relationships between an intervention and its intended outcomes by controlling for other factors that could affect the outcomes (York and Bamberger 2020). It is an approach taken due to the belief that drawing upon the correlation between variables does not provide practical utility for policymakers (York and Bamberger 2020). By contrast, data scientists utilise various techniques on constantly updating large datasets which cover a wide range of variables to create predictive means of assessing how certain groups are most likely to respond

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to specific interventions (York and Bamberger 2020). This approach allows data scientists to detect real-time relationships that conventional M&E tools could not or were not designed to detect.

The ability to utilise predictive analytics is due to large datasets being able to adequately represent the total population size. Though challenges exist with this assertion, such as selection bias, data quality, and the proprietary algorithms used to generate this data, improvements in this sector seek to address these concerns (York and Bamberger 2020). Increased datafication allows for techniques such as data mining, computational analysis, and predictive modelling on large datasets to make informative and reliable predictions.

M&E specialists and data scientists also potentially clash regarding epistemology. Public policy is generally theory-driven, and monitoring is restricted to a predefined set of indicators. With data science and the increase in data volumes and processing power, we can expand this set of indicators and monitor spillover effects outside of the target sector or population. Conditional cash transfer, education, and health programmes often target the poor. However, the poor are often a subset of a local economy, loosely defined as the geographical unit within which the poor live, such as the city, the municipality, the neighbourhood, or the household.

Programmes may also affect non-target populations. For example, conditional cash transfer recipients may purchase goods and services from ineligible households, thus contributing to their livelihoods. Similarly, children who receive free textbooks and computers may share them with other children (e.g., relatives and friends), thereby increasing their enrolment. Finally, supplying deworming drugs to the most exposed children may also benefit the less exposed children by reducing disease transmission and lowering infection rates. Sometimes these spillover effects are predicted. Often, they are not, which means they are unlikely to be detected using traditional, deductive monitoring. Inductive monitoring presents its own methodological challenges. While we can detect changes, we generally cannot attribute changes to a specific programme. In other words, we may have suggestive evidence that project X had spillover effects on target sector or population Y. However, we cannot prove that X caused Y.

Towards Algorithmic Governance

Governance broadly relates to the coordination of social interactions through the production and implementation of ideas, plans, regulations, and policies concerning the public to solve collective action problems (Gritsenko and Wood 2020). It is argued that the increase in data volumes, the changing nature of data, and the improvements in processing power have implications for governance in general, and monitoring. As public institutions embrace the opportunities brought by datafication, new challenges emerge against established means of governance.

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The evolution of governance during both the 20th and early 21st centuries has been predicated on the need for the state to produce new solutions to problems created by changing social and economic conditions within society. Though the form and focus of these reforms in the public sector differ worldwide, the reforms remain a shared experience and are often seen as a means to multiple ends (Pollitt and Bouckaert 2017). Whether these ends relate to creating savings in public expenditure, improving the quality of public service, creating more efficient government operational and administrative systems, or improving the effectiveness of government interventions, the need for change is imperative (Pollitt and Bouckaert 2017). Even though M&E has had its own evolutionary path as a discipline in its own respect, the rearrangement of public institutions and administrative processes over time has influenced the usage of M&E tools at the public servants' disposal. What remains consistent is that decision-makers who build programmes intended to create social reforms rely on relevant and usable knowledge (Head 2008). However, as the nature of relevant and usable knowledge experiences exponentially increases, it begs the question of how governance should alter itself to accommodate these changes.

Industry 4.0 (I4.0) refers to the integration of information and operational technologies in a manner that transforms the production processes and "takes advantage of the abundant information available in each stage of the value chain, from suppliers to customers, of any industrial sector (manufacturing, energy, transport, supplies, mining, health, pharmaceutical, etc.)" (Zorrilla and Yebenes 2022:1). I4.0 can be expanded towards the public sector. The impact of the transformations caused by I4.0 has necessitated the integration of a ubiquitous level of connectivity between data, people, processes, and services, where all of these elements exchange and exploit each other's information, leading to further increase in both the amount and variation of data generated in real-time (Zorrilla and Yebenes 2022). These advancements in digital technologies and datafication have ensured that there has been an increased level of "information-based steering of activities", often with the intent of creating greater levels of coordination when trying to solve complex societal problems (König 2020:469). These activities refer to the generation, transfer, storage, and processing of information through networked interactions characterised by the "co-presence of manifold entities which can dynamically adjust their behaviours" (König 2020:469).

Datafication and the increased networks of stakeholders working on societal issues have necessitated a new form of governance: algorithmic governance. Algorithmic governance refers to the usage of fine-grained information generated from various entities that allow for the finding of patterns in the behaviours and interactions of these entities with the final intent of coordinating these behaviours in the future (König 2020). It refers to the organisation of society and the economy by reiterating step-by-step processes and/or rules that determine how inputs are processed into outputs. It results in a form of governance less focused on administrative processes, but rather the governance of public services using knowledge about "service users

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and citizens that is collected from them in order to govern them more effectively" (Williamson 2014:3). Governance then becomes a set of "processes of decentralised coordination of distributed entities" whose changing behaviour feeds back into the algorithmic decision-making system so that the behaviours of the other entities or agents can be attuned to these information updates (König 2020).

The shift to algorithmic governance signifies the intent by the state to contend with developments within society ranging from the analysis of "big data' generated from transactional processes, peer production, the democratisation of innovation, crowdsourcing, wikinomics, cognitive surplus, and network effects" (Margetts and Dunleavy 2013). Data in and of itself is value neutral. Nevertheless, as an input for algorithms, it can have both intended and unintended consequences due to data only providing a partial view of the world. As a result, its generation and interpretation may be biased or incomplete, or might be deliberately or accidentally manipulated before ever being used (Janssen & Kuk 2016). Regardless, the resultant shift to algorithmic governance has created the ability to design governance structures that utilise data about human-human and human-state interactions to create tailored policy interventions or predictions that meet the desires and interests of citizens in real-time (Gritsenko and Wood 2020).

In the past, these designs were limited to the dominant paradigm of the time. With algorithmic governance, these designs can be made to be hierarchical (the traditional model), self-governed (new public management through increased disaggregation), or co-governed (networked governance), depending on what the state requires. This is due to algorithmic governance allowing for the choice of governance architecture that can structure the decision situations of individuals within the public sector by providing "certain information, options, and suggestions, thereby making some choices more and others less likely" (Yeung 2017).

Three Broad Challenges

Algorithmic governance poses three broad challenges for monitoring (Gritsenko and Wood 2020). The first is automated decision-making. In traditional monitoring systems, decisions are taken by individuals who can be held accountable. Institutional arrangements inform these accountability structures at both a political and institutional level. By contrast, in automated decision-making systems, accountability is subverted, and monitoring is opened to various challenges such as automation bias, the deprivation of humans as agents of judgement and reason, and the development of self-perpetuating echo chambers (Gritsenko and Wood 2020). Furthermore, automated decision-making ensures that the human element no longer functions within the traditional causal linkages provided by statistical analysis. The M&E specialist no longer plays a central controlling role regarding what variables are "compared and combined to generate predictive outputs" (Appel and Coglianese 2020:166).

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The second broad challenge is the invisibility of decision-making. This poses a renewed challenge on monitoring by providing a means of decision-making that may usurp public interest (Gritsenko and Wood 2020). Though a policy's political mandate may be unambiguous, the circumvention of public interest through automated decision-making based on data generated by citizens, businesses, or the state entails altering a policy in a manner that may deviate from its original intent. Without traditional structures of accountability, this alteration creates a "black box society" where the changes to policies are not reliant on changes in public interest, but rather the changes observed by what may seem to be ambiguous algorithmic determinations of what is, or may be, of interest to the public. As Appel and Coglianese (2020:167) explain, the black box of algorithmic governance is the result of the inherent difficulty in explaining how the outputs are generated to the public and the inability to ascribe a "causal relationship between an algorithm's input data and its output prediction".

The third broad challenge relates to ethics. Though data may be politically neutral, the choices and base assumptions that inform algorithmic processes are informed by the designers of these algorithms, creating a wide variety of intended and unintended consequences that pose specific ethical questions (Gritsenko and Wood 2020). Though automated decisions based on algorithms may be happily accepted when creating efficiencies within a postal office, it is unclear how these decisions would be accepted regarding decisions related to the criminal justice system (Appel and Coglianese 2020).

Democratic Governance or Technocratic Solutionism

The three broad challenges posed above, brought about by datafication and the emergence of algorithmic governance, bring an old debate to the forefront which involves the balance between democratic governance and technocratic solutionism. M&E specialists, at both the policy implementation and the data generation level of analysis, must contend with the need to develop tools to assess and monitor technical solutions related to algorithmic interventions within the state while also assessing the democratic efficacies of these interventions. These solutions relate to automated decision-making interventions and predictive analytics that utilise data from "official records and statistics; secondary data obtained through administrative operations from frontend services; user-generated data often in the form of web content such as blogs, chats, tweets and videos; sensory data gathered by connected people and devices; tracking data such as CCTV, GPS, or traffic data, as well as satellite and aerial imagery; and transaction data from shopping or banking records" (Engin and Treleaven 2019:450). It also extends to solutions centred on the examination of big data to discover hidden patterns and undiscovered correlations within government interventions (Engin and Treleaven 2019).

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At an institutional level, assessing the technical efficacies of algorithmic governance will increasingly fall upon the shoulders of M&E specialists and data scientists who will need to work in tandem to devise appropriate tools to monitor and assess algorithmic programmes. Though room will still exist for traditional approaches to governance, increased automation in decision-making, rapid increases in data generation and processing capabilities, and the predictive power of algorithmic approaches to monitoring will demand a new set of skills from M&E specialists. Skills will also require the support of reimagined governance mechanisms that better understand the relationship between human evaluators and computational code.

From a democratic perspective, algorithms remain inherently relational and reliant on human intuition. It involves balancing an intricate and dynamic arrangement of people and code where M&E specialists and data scientists work on the design and implementation of algorithmic logic (Janssen and Kuk 2016). As a result, the role of M&E specialists will be fixed in the macro-political context of monitoring and evaluating. Creating democratic accountability measures for algorithms depends on various social and political contexts and relies on certain systemic factors such as political will, effective legal institutions, and the rule of law (Basu et al. 2021).

From this democratic perspective, the monitoring of algorithmic interventions relies on two general focus areas. The first relates to monitoring the adoption and implementation of algorithmic interventions and their consistency with the existing legal framework. M&E specialists within this space will be responsible for monitoring how algorithmic interventions remain aligned with an existing mechanism of administrative accountability. However, noting the rate at which the sector is evolving and the ambiguity of the potential scope of these interventions, it bears noting that specific interventions may not yet have clear legislative guidelines. Therefore, evaluators must be responsible for the identification of algorithmic interventions that deviate from democratic principles enshrined by overarching forms of legislation, such as constitutional frameworks and the various degrees of scrutiny applied to various algorithmic systems (Basu et al. 2021).

The second general focus area relates to transparency. The transparency of algorithmic systems will become dependent on the reporting done by monitoring systems specifically designed for these interventions. Transparency relates to the "specific decisions made about particular individuals or groups, as well as more general concerns around how the use of algorithmic systems is contributing to the function of particular public agencies, including policy-making and administrative functions" (Basu et al. 2021:45).

Due to the nascent nature of algorithmic governance within the continent, providing details of uses cases is difficult, and as a result, literature that provides deeper insights into its implication is scarce. That said, one case can be briefly discussed. This case involves Nigeria's implementation of its Rapid Response Register (RRR), which forms part of the federal government's Economic Sustainability Plan and the

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National Social Protection Policy (Adeyeye 2022:11). The RRR functions as a means to scale the National Social Safety-Nets Programme and improve the standard of living of 100 million Nigerians identified as living in poverty (Apera et al. 2021:36). Utilising a combination of remote sensing, machine learning, and big data analysis that improves upon the traditional data sources previously used by the state, the RRR ranks urban poor wards according to their patterns of wealth and poverty (Apera et al. 2021:39). The use of these technologies provides the means for geographic targeting and poverty mapping that when used in conjunction with SMS and USSD application processes linked to mobile phone numbers, and the system provides the means for communities to self-register and enrol as beneficiaries of the RRR (Apera, Daniel, Balogun et al. 2021:40). The system improves the identification strategies of households eligible for government funded cash transfers, with validation of these households undertaken through SMS-based applications (Lowe, McCord and Beazley 2021:21). The system differs from traditional approaches to monitoring cash transfer systems as it is less reliant on community inputs collected by surveyors, but functions through the assessment of previously collected data validated through geographic targeting of citizen responses (Lowe et al. 2021:28).

The combination of these various technologies led to an overall improvement of cash transfers with 95% of identified eligible participants being both registered on the system and provided with a cash transfer (Apera et al. 2021:41). The targeting approach undertaken by the RRR was the first of its kind within sub-Saharan Africa and will be used to further scale Nigeria's other social protection initiatives and interventions (Apera et al. 2021:41). It further showcases the use of automated decision-making as a replacement for traditional methods of monitoring household wealth within urban poor regions in West Africa.

Conclusion

Datafication is changing our societies. It has already changed how public institutions operate, including the way in which policies are developed and implemented, and how public services are delivered. However, it has not yet fundamentally affected the monitoring of these policies. The potential is enormous. The utilisation of big data to monitor the performance of different policies and public institutions is one of the most exciting promises of the 'data age'. This chapter has discussed the opportunities and challenges associated with greater data utilisation in public sector monitoring. Three drivers of datafication were highlighted – the increase in data volumes, the changing nature of data, and the improving processing power of computers – which fundamentally change the context within which monitoring occurs. The realignment will require closer collaboration between M&E specialists and data scientists, who work within different institutional cultures and face epistemology and research methods in fundamentally different ways. Bringing them together will be an important challenge to overcome in the era of algorithmic governance.

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