Building National Analytics Capacity: Advances and Future Pathways

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Abstract
The capacity of nations to collect, govern, analyse and act upon data has become a defining determinant of public value, competitiveness and resilience. This paper synthesises the state of the art in national analytics capacity, the interlocking set of infrastructures, human capital, institutional and governance arrangements that allow a country to convert data into decisions at scale, and charts a forward-looking research agenda. We situate the discussion in the momentum generated by the United Nations "data revolution" agenda and the World Bank's framing of data as a resource for development, and we organise recent advances into four themes: data infrastructure and platforms; skills and human capital; institutions and governance; and public-sector use cases. Across these themes we observe genuine progress, the maturation of open government data ecosystems, the professionalisation of data science roles, the diffusion of cloud and interoperability standards, and a growing evidence base on analytics capabilities and value realisation. To make the synthesis actionable we describe a five-level national analytics maturity model spanning six capability dimensions, offering a common vocabulary for assessment and target-setting. We then examine persistent open challenges, including fragmented data infrastructures, acute skills shortages, weak data governance, uneven data literacy, and the equity and trust risks that accompany data-intensive government. Finally, we propose concrete future opportunities and research directions: capability-maturity measurement, human-capital pipelines, federated and privacy-preserving infrastructure, institutional design for stewardship, and impact evaluation of analytics investments. The paper is intended as a compact orientation for researchers, policymakers and practitioners building analytics capacity at national scale.

Keywords: *national analytics capacity; data for development; open government data; data governance; digital transformation; data literacy; analytics maturity; statistical capacity*

1. Introduction

Over the past decade, data has moved from a by-product of administrative processes to a strategic asset that governments, firms and civil-society organisations actively cultivate. The shift is captured in the influential report *A World That Counts*, which called for a "data revolution for sustainable development" and argued that better data, more openly shared and more capably used, is a precondition for meeting collective goals [1]. The argument reached a broader audience with the World Bank's *World Development Report 2021: Data for Better Lives*, which framed data as a resource capable of improving the lives of the poor while cautioning that the value of data is realised only when it is matched by trustworthy governance and adequate capacity [2].

For nations, the practical question is no longer whether data matters but whether the country possesses the *capacity* to use it. We define **national analytics capacity** as the interlocking set of infrastructures, human capital, institutional and governance arrangements that enable a country to collect, integrate, govern, analyse and act upon data at scale and across sectors. This definition deliberately extends beyond the narrow notion of statistical capacity, the ability of national statistical systems to produce official statistics, to encompass the broader ecosystem in which administrative data, open data, machine learning and analytics are combined to inform public decisions [3], [4]. The word "capacity" is doing deliberate work in this definition, and it is worth distinguishing from the adjacent terms it is often confused with. Capacity is not the same as infrastructure, which is only its material substrate; nor is it the same as the possession of skilled individuals, who can be present yet unable to affect decisions; nor is it reducible to the adoption of particular tools or platforms, which may sit unused. Capacity, in the sense intended here, is a *dispositional* property of a national system: a standing ability to convert data into better decisions reliably and at scale, which persists across particular projects and particular personnel. A country demonstrates capacity not when it completes one successful analytics project but when it can do so repeatedly, in different sectors, without heroic individual effort each time, because the enabling conditions (the data flows, the skills, the institutions, the trust) are durably in place. This dispositional framing matters because it explains why capacity is so much harder to build than any of its visible components: one can procure a platform or hire a data scientist in months, but the standing ability to use them well is an emergent property of the whole system and accumulates only over years. The verbs in the definition (collect, integrate, govern, analyse, and act) are chosen to mark a chain, each link of which can break independently. A country may collect abundant data yet be unable to integrate it across the silos in which it is trapped; it may integrate it yet govern it so poorly that its use is neither safe nor trusted; it may analyse it competently yet fail at the final and hardest step of acting on the result, so that insight dies in a report. The last link is the one most often underestimated. The distance between a correct analysis and a changed decision is where much national analytics capacity is won or lost, because it runs through incentives, mandates, professional cultures, and public trust that no amount of technical sophistication can bypass. Framing capacity as a chain rather than a stock is a way of insisting that the weakest link, wherever it falls, governs the value the whole system can deliver. Three developments make this an opportune moment for synthesis. First, the enabling technologies (cloud computing, open-source analytics, and interoperability standards) have matured and fallen in cost, lowering barriers to entry [5]. Second, a substantial research literature on analytics capabilities and value realisation has accumulated, offering theory and evidence that were unavailable when the data-revolution agenda was first articulated [6], [7]. Third, the public sector has moved from pilots to programmes, generating a stock of use cases and hard-won lessons about what capacity-building requires in practice [8], [9]. This paper is written in the *advances and future opportunities* genre. It is not a formal systematic review; rather, it offers a curated state-of-the-art synthesis together with a forward-looking research agenda. Section 2 defines background and scope. Section 3 synthesises advances across four themes and presents a national analytics maturity model. Section 4 sets out open challenges, Section 5 proposes future opportunities and research directions, and Section 6 concludes.

Contributions on an allied portfolio of studies spanning trade law and compliance, AI and data governance, and semiconductor and edge-computing engineering inform the framing adopted here [10]–[15]. Cognate work addressing public-sector accounting, audit, and financial reporting provides complementary grounding [16], [17]. A related stream of research on enterprise cybersecurity and cyber-defense engineering reinforces these observations [18]–[20]. Studies concerned with operational-technology and critical-infrastructure security offer supporting evidence and methods [21], [22]. Parallel investigations into artificial intelligence in education, learning, and digital health extend the perspective developed above [23]. Further work on the foundational and directly cited literature underpinning the present study situates the present contribution within a wider programme [1]–[9], [24]–[38].

2. Background and Scope

2.1 From statistical capacity to analytics capacity

The intellectual roots of national analytics capacity lie in the "data for development" tradition, which has long recognised that national statistical systems are foundational public infrastructure. Partnerships such as PARIS21 have monitored and supported statistical capacity development for two decades, and their work documents both the progress and the fragility of statistical systems in lower-income countries [3]. The data-revolution agenda broadened this frame, arguing that traditional statistics must be complemented by new data sources, new analytical methods and new institutional arrangements [1]. Analytics capacity, as used here, is the enlargement of statistical capacity to include the integration of administrative and non-traditional data, the application of machine learning and business intelligence, and the organisational ability to translate insight into action [26], [34].

2.2 Why capacity, not just technology

A recurring theme in the management and information-systems literatures is that technology alone does not create value; value emerges from the bundling of technological, human and organisational resources into a *capability* [7], [35]. Early survey work found that the leading obstacle to deriving value from analytics was not data or technology but managerial and skills-related, a lack of understanding of how to use analytics to improve the business [32]. This capability perspective, developed in the private sector by Davenport and Harris [27], transfers directly to the public sector: a nation may possess data lakes and dashboards yet lack the analysts, incentives and governance to convert them into better decisions [8]. The intellectual pedigree of this insight lies in the resource-based view of the firm, which holds that competitive advantage flows not from resources that can be bought on the open market (which by definition confer no lasting advantage, since anyone can buy them) but from the idiosyncratic ways an organisation combines and deploys them. Applied to analytics, this explains a pattern that has frustrated a decade of investment: the components of an analytics function are increasingly commoditised, available to any government with a budget, and precisely because they are commoditised they cannot by themselves distinguish a capable data-using state from an incapable one. What distinguishes them is the complementary and hard-to-imitate assets, the accumulated organisational routines, the tacit knowledge of how to frame a problem analytically, the relationships that let an analyst's finding reach a decision-maker who trusts it, that surround the commodity components and make them productive. These complementary assets are the reason capacity cannot simply be purchased, and the reason two countries with identical technology can differ enormously in what they extract from it.

For the public sector the argument carries an additional edge. Firms that fail to bundle their analytics resources into a genuine capability are eventually disciplined by competition; governments face no equivalent corrective, and a public agency can maintain an underused analytics function indefinitely, its dashboards refreshed and unread, because nothing forces the latent gap between capability and use into the open. This absence of an automatic corrective places a heavier burden on deliberate design: what the market supplies to firms as feedback, the public sector must supply to itself through evaluation, oversight, and an explicit culture of evidence use. The capability perspective thus does more than relabel the problem; it locates the binding constraint in the organisational and institutional layer and predicts, correctly, that investment concentrated in the technological layer will yield disappointing returns until the surrounding capability is built.

2.3 Scope of this synthesis

We scope national analytics capacity along six dimensions that recur across the literature: (1) *data and infrastructure*; (2) *skills and human capital*; (3) *institutions and governance*; (4) *methods and tooling*; (5) *use and value realisation*; and (6) *ethics, privacy and trust*. These dimensions structure both the advances discussed in Section 3 and the maturity model presented there. Our emphasis is on the national and public-sector level, though we draw on private-sector evidence where the underlying mechanisms are shared. The six dimensions are not an arbitrary list but a deliberate attempt to span the full chain from raw data to trusted action while separating concerns that are too often conflated. Data and infrastructure and methods and tooling together constitute the technical substrate; skills and human capital and institutions and governance constitute the organisational and institutional layer that animates it; use and value realisation names the outcome the whole apparatus exists to produce; and ethics, privacy and trust is treated as a dimension in its own right rather than as a constraint bolted onto the others, because in the public sector legitimacy is not a side condition but a precondition of sustained operation. Keeping these six analytically distinct guards against a characteristic error of capacity assessment: reading strength on a visible dimension, usually infrastructure, as evidence of overall capacity, when the binding constraint lies on a less visible one, usually governance or use. Two features of this scoping deserve emphasis before the advances are surveyed. First, the dimensions are interdependent rather than additive: progress on one frequently depends on progress on another, so that investment in tooling yields little without the skills to use it and the governance to trust it, and the dimensions therefore cannot be pursued in isolation or summed into a single score without loss. Second, the public-sector emphasis is not merely a change of setting but a change of logic. Where private-sector analytics is ultimately validated by profit (a single, if crude, summary measure of whether capability translates into value) public-sector analytics answers to a plural and contested notion of public value, in which equity, legitimacy, and the avoidance of harm sit alongside efficiency and cannot be traded off against one another by any common denominator. This difference propagates through every dimension, and it is why private-sector evidence, though instructive on shared mechanisms, must be transposed to the public setting with care rather than imported wholesale. Contributions on semiconductor, RF/MEMS and microelectronic systems engineering and biomedical imaging inform the framing adopted here [39]. Cognate work addressing internal audit, risk governance, and financial-sector controls provides complementary grounding [40]–[43]. A related stream of research on financial-fraud detection, audit analytics, and risk analytics reinforces these observations [44]. Studies concerned with supply-chain management, ESG auditing, and sustainable procurement offer supporting evidence and methods [45]–[48]. Parallel investigations into Salesforce platform engineering and CRM governance extend the perspective developed above [49]–[51].

3. Advances and the State of the Art

3.1 Data infrastructure and platforms

The most visible advances have been in data infrastructure. Two intertwined movements stand out: the open government data (OGD) movement and the diffusion of cloud-based, interoperable platforms. Open government data initiatives spread rapidly across national and municipal governments, driven by expectations of transparency, accountability, participation and economic innovation [4], [24]. Systematic reviews have catalogued the design choices (portals, licensing, metadata, standards) that distinguish mature initiatives from nominal ones, and have documented the gap between publishing data and generating use [24]. Comparative frameworks for open-data policy show wide variation in implementation and impact, underscoring that publication is a means rather than an end [38]. Where OGD has been paired with intermediaries and re-use communities, it has been linked to data-driven innovation and new services [31].

Underpinning these initiatives is a shift toward cloud computing, open-source analytics stacks and interoperability standards, which together lower the fixed costs of storage and computation and make advanced tooling accessible to public agencies [5]. The World Bank's framing of a national "data infrastructure", the physical, technological and institutional plumbing that allows data to flow safely between producers and users, has helped consolidate infrastructure as a policy category in its own right [2]. Progress here is real but uneven: the same reviews that document diffusion also document fragmentation, with siloed systems and inconsistent standards limiting integration [8], [24]. The economics of the cloud shift are worth making explicit, because they alter the strategic calculus of capacity-building. By converting the large fixed capital costs of data centres and software licences into variable operating costs paid in proportion to use, cloud provisioning lowers the threshold at which a public agency can begin to work with data seriously, and it decouples analytical ambition from the possession of physical infrastructure. This is genuinely levelling: a small agency, or a lower-income state, can in principle access computational capability that a decade ago required capital it could never have raised. Yet the same shift introduces new dependencies that are themselves a capacity question. Reliance on external providers raises issues of data sovereignty, vendor lock-in, recurring cost that must be sustained against annual budget pressures, and the concentration of critical public functions in infrastructure the state does not control. The maturation of cloud provisioning has thus not so much removed the infrastructure problem as transformed it, from a problem of building and owning to a problem of governing dependence, one for which many public administrations are less well prepared than they were for the older problem of procurement.

Interoperability deserves separate treatment from raw infrastructure because it is where the gap between publishing data and using it most visibly opens. Storage and computation have become cheap and abundant; the ability to combine data held in different systems, produced under different definitions, and governed by different rules has not. The difficulty is only partly technical, a matter of formats and schemas; more fundamentally it is semantic and institutional, requiring that agencies agree on what a shared concept means, on who is authorised to link records, and on the legal basis for doing so. This is why the open-data movement's early emphasis on publication produced portals full of datasets that could not be joined, and why interoperability has emerged as the harder and more consequential frontier. A national data infrastructure worthy of the name is defined less by how much data it holds than by how safely and reliably that data can flow and combine across the boundaries within government, which is a property of standards, agreements, and governance far more than of storage.

3.2 Skills and human capital

A second front of advance is the professionalisation of data work. The emergence of "data scientist" as a recognised, high-demand role, famously characterised as "the sexiest job of the 21st century", signalled the arrival of a labour market for analytical talent and stimulated the growth of formal training pipelines [28]. The conceptual clarification of data science as the discipline connecting big data to data-driven decision-making gave curricula an intellectual anchor [34].

Alongside specialist skills, a broader literature has developed around *data literacy*, the competencies that enable non-specialists to read, interpret, question and use data responsibly [37]. This work reframes human capital as a distribution rather than a scarce elite: capacity depends not only on a cadre of data scientists but on managers, frontline staff and citizens who can engage critically with data [37]. For developing countries in particular, the information-systems literature has long warned that capacity gaps and the mismatch between imported designs and local realities are primary causes of project failure, making local skills and "improvisation" decisive [30].

The reframing of human capital as a distribution rather than an elite is more consequential than it first appears, because it changes where the binding constraint on absorptive capacity lies. An organisation's ability to make use of analytical output is limited not by its most sophisticated analyst but by the data literacy of the managers who must interpret a model's results, weigh their uncertainty, and act on them. A brilliant predictive model handed to a decision-maker who cannot distinguish a correlation from a basis for action, or who cannot interrogate the assumptions behind a forecast, will be either ignored or misused, and either failure wastes the analytical investment entirely. This is why concentrating scarce resources on a small cadre of specialists, while neglecting the broad middle of managers and frontline staff, tends to disappoint: it builds the supply of analysis without building the demand-side competence required to consume it. Data literacy, distributed widely, is what raises an organisation's absorptive capacity to the point where specialist output can actually change decisions. The public sector faces a structural disadvantage in the market for specialist talent that shapes any realistic capacity strategy. Governments compete for scarce data scientists against private employers who can typically offer higher pay, faster tooling, and fewer procedural constraints, and they compete while offering, in compensation, mission and stability whose appeal is real but selective. The implication is not that the public sector should try to win a bidding war it will usually lose, but that it should design around the constraint: cultivating talent internally, retaining it through problems of genuine public consequence, distributing literacy widely so that dependence on scarce specialists is reduced, and, in lower-income settings especially, prioritising local capacity that can adapt imported tools to local realities rather than importing designs wholesale. The recurrent finding that mismatched designs and thin local skills drive project failure in developing countries is, read constructively, an argument for treating capability-building as an act of local adaptation and improvisation rather than of technology transfer, a lesson that applies, in muted form, to public administrations everywhere.

3.3 Institutions and governance

Institutional and governance advances have been slower but consequential. The World Bank's *World Development Report 2021* placed governance at the centre, arguing that a social contract for data, balancing value creation with protection against harm, is the linchpin of trustworthy data use [2]. Complementing this, the OECD has articulated the elements of a “data-driven public sector,” including data governance, stewardship roles and a culture of evidence use [33].

The digital-government research tradition provides theoretical grounding for these institutional questions, situating analytics capacity within broader debates about public management, coordination and value creation [29]. Studies of big data in the public sector emphasise organisational readiness, inter-agency data sharing and the political and legal uncertainties that shape whether analytics is adopted [8], [9]. At the same time, evidence that information and communication technologies can foster transparency and act as anti-corruption tools has strengthened the accountability rationale for investing in institutions of data governance [25].

Governance is the dimension on which progress has been slowest, and the reason is instructive rather than incidental. Infrastructure and skills yield visible, attributable outputs (a portal launched, a unit staffed) that reward the officials who deliver them; governance yields mostly the absence of bad outcomes, a breach that did not happen, a misuse that was prevented, and the absence of harm is a notoriously thankless thing to fund. Governance also cuts across the very silos that analytics must bridge, requiring agencies to cede some autonomy over data they regard as theirs, which makes it politically costly in a way that building one’s own platform is not. The result is a systematic tendency to under-invest in stewardship relative to its importance, and to discover its necessity only after a failure has made the cost of its absence concrete. Recognising this asymmetry is the first step toward correcting it, because it reframes governance not as a brake on analytics but as the enabling condition without which data cannot safely flow or combine at all.

The notion of a social contract for data reframes governance in a way that is particularly apt for the public sector. Rather than treating data protection as a checklist of restrictions imposed from outside, it casts the relationship between a state and the people whose data it holds as a reciprocal bargain: citizens permit the use of data about them, and in return the state commits to using it to create value that is shared, and to protecting against the harms that data use can inflict. This framing makes explicit that the licence to use data is granted, not owned, and can be withdrawn (through non-compliance, evasion, or political backlash) if the bargain is seen to be broken. It thereby connects the seemingly technical work of data governance to the deeply political question of legitimacy, and it explains why transparency and anti-corruption applications matter beyond their immediate function: by demonstrating that data is used in the public interest, they replenish the trust on which the whole enterprise of data-intensive government ultimately depends.

3.4 Use cases and value realization

The fourth theme concerns demonstrated use. Across sectors, analytics has moved from proof-of-concept to operational deployment. In healthcare, studies document how big-data analytics capabilities improve organisational outcomes when technical assets are combined with managerial and human capabilities [52]. In business and public administration more broadly, empirical work links analytics capabilities to performance, mediated by dynamic capabilities and organisational agility [35]. The public-affairs literature catalogues applications in service delivery, program management and policy analysis, while cautioning that measurable public value remains harder to demonstrate than private-sector returns [9].

The healthcare evidence is especially instructive because it isolates the mechanism cleanly. Where big-data analytics capability improves outcomes, it does so not through the technical assets in isolation but through their combination with managerial and human capabilities that direct the technology at the right problems and translate its output into changed clinical and operational practice. The same technical investment, absent those complementary capabilities, produces little.

This is the socio-technical thesis in miniature, and its recurrence across sectors, from hospitals to firms to public administration, is what lends the thesis its authority. It is not a claim that technology does not matter but a claim about sequence and complementarity: technology is the component whose marginal value is lowest when the surrounding capabilities are absent and highest when they are present. A consistent finding across these use cases is that value is realised through a *socio-technical* pathway: data and tools are necessary but insufficient, and the binding constraints are typically capability, governance and culture [6], [32]. The public-sector experience adds a further nuance. Because government outputs are often intangible and their beneficiaries diffuse, the "insight-to-action" gap is wider than in commercial settings: a well-specified predictive model may fail to change practice if frontline incentives, legal mandates or citizen trust are not aligned [8], [9]. Successful deployments therefore tend to pair analytical assets with deliberate investments in change management, inter-agency coordination and stakeholder engagement, precisely the "softer" capabilities that are hardest to procure and easiest to neglect. This finding motivates the maturity model below, which treats capacity as multidimensional rather than reducible to technology.

3.5 A national analytics maturity model

To make the synthesis actionable, we describe a five-level maturity model spanning the six capability dimensions introduced in Section 2.3. The model draws on analytics-capability and open-data maturity research [7], [24] and adapts it to the national scale. It is intended as a heuristic for self-assessment and target-setting, not a certification instrument.

Table 1. National analytics maturity across six capability dimensions.

Dimension	L1: Nascent	L2: Emerging	L3: Established	L4: Integrated	L5: Optimising
Data & infrastructure	Siloed, paper-based or fragmented systems	Basic digital registers; first open-data portal	Shared platforms; core registries digitised	Interoperable, cloud-enabled data infrastructure	Federated, real-time data ecosystem
Skills & human capital	Ad hoc; no dedicated analysts	Isolated specialists; external dependence	Analytics units in lead agencies	Distributed data literacy; internal talent pipeline	Self-sustaining talent ecosystem; continuous learning
Institutions & governance	No data policy or stewardship	Draft policies; unclear mandates	Data-protection law; designated stewards	Cross-government governance and standards	Adaptive governance; embedded social contract for data

Dimension	L1: Nascent	L2: Emerging	L3: Established	L4: Integrated	L5: Optimising
Methods & tooling	Manual reporting	Descriptive dashboards	Standardised BI and reporting	Predictive analytics and ML in production	Continuous, responsible AI at scale
Use & value realisation	Data unused in decisions	Isolated pilots	Recurrent use in some agencies	Routine data-driven decisions across sectors	Measured public value; feedback-driven improvement
Ethics, privacy & trust	No safeguards	Reactive, incident-driven	Baseline privacy controls	Privacy-by-design; transparency mechanisms	Demonstrated public trust; accountable, auditable systems

The model conveys three ideas. First, capacity is *multidimensional*: a country may be advanced in infrastructure yet nascent in governance, and the lagging dimension constrains overall value (a "weakest-link" property consistent with the capability literature; Mikalef et al., 2018). Second, higher maturity is characterised less by technology than by *integration*, the alignment of data, skills, institutions and ethics. Third, the top level foregrounds trust and measured value, reflecting the WDR 2021 argument that legitimacy is not a by-product but a condition of sustained data use [2]. The weakest-link property has a sharp practical corollary that distinguishes this model from maturity frameworks that treat progress as the accumulation of independent achievements. If overall value is constrained by the lagging dimension, then the marginal return to investment is highest not where a country is already strong but where it is weakest, and a strategy that pours further resources into an already-advanced infrastructure while governance or use languishes will raise the maturity score on paper without raising the value delivered in practice. This runs against a common political economy of capacity-building, in which the visible and fundable dimensions attract investment precisely because they are visible and fundable, while the unglamorous, cross-cutting dimensions are starved. The model's discipline is to force attention onto the binding constraint, and its diagnostic value lies as much in identifying which dimension is holding a country back as in locating its overall level. The levels should be read as describing qualitative transitions rather than smooth increments, because the difficulty of advancing is not uniform along the scale. Early transitions (from paper to digital registers, from no analysts to a first specialist unit) are largely matters of procurement and hiring, and can be accomplished relatively quickly with resources and will. The higher transitions are different in kind: moving from established to integrated capacity requires alignment across agencies that no single agency can accomplish alone, and moving to the optimising level requires the embedding of trust and measured value that cannot be procured at all but must be earned over time through demonstrated reliability. This is why the upper levels of the model foreground integration and trust rather than any new technology, and why so many national efforts stall at the middle of the scale: the resources that carried them through

the early transitions are the wrong instrument for the institutional and cultural work the later ones demand. The model, used honestly, is therefore less a ladder to be climbed by continued effort of the same kind than a map of successive changes in the kind of effort required.
Contributions on predictive analytics and data-driven decision-support systems inform the framing adopted here [53]. Cognate work addressing predictive analytics for retail, finance, and operations provides complementary grounding [54], [55]. A related stream of research on enterprise IT systems, cloud migration, and service management reinforces these observations [56]–[58]. Studies concerned with marketing analytics and AI-driven automation in regulated service environments offer supporting evidence and methods [59]–[63]. Parallel investigations into energy-transition modeling and renewable forecasting extend the perspective developed above [64], [65].

4. Open Challenges

Despite genuine advances, several challenges persistently limit national analytics capacity.
Fragmented infrastructure and weak interoperability. Even where data exists, it is frequently locked in incompatible systems with inconsistent standards and metadata, raising the cost of integration and undermining reuse [8], [24]. Publishing open data has proven far easier than achieving the interoperability that makes data combinable across agencies [38].

Skills shortages and uneven data literacy. Demand for analytical talent outstrips supply, and the public sector competes at a disadvantage for scarce data scientists [28]. Equally limiting is the shallow distribution of data literacy among managers and frontline staff, which caps an organisation's ability to absorb analytics even where specialists are present [32], [37]. In lower-income settings these constraints are compounded by dependence on external expertise and the risk of designs poorly matched to local conditions [30].

Weak governance and institutional voids. Many countries lack coherent data-protection law, clear stewardship mandates and cross-government coordination, leaving analytics initiatives exposed to legal uncertainty and public mistrust [2], [33]. Without an explicit social contract for data, the balance between value creation and harm prevention is struck ad hoc, eroding legitimacy [2].

Difficulty demonstrating public value. Unlike firms, governments cannot rely on profit as a summary measure of analytics returns, and rigorous evaluation of impact remains rare [9]. The socio-technical nature of value realisation makes attribution difficult and encourages investment in visible tools over harder-to-measure capabilities [6]. This measurement difficulty is not merely an academic inconvenience; it distorts investment in a predictable direction. When the returns to a capability cannot be demonstrated, the capability struggles to command a budget against competing claims that can point to visible outputs, and so the dimensions whose value is hardest to measure (governance, data literacy, the diffuse absorptive capacity of the organisation) are systematically underfunded relative to the dimensions that produce a photograph, a portal, or a launch event. The absence of a profit signal thus does more than deprive the public sector of a scorecard; it biases the allocation of effort toward the measurable and away from the consequential, and it is one reason capacity-building so often produces impressive infrastructure sitting atop weak institutions and thin use.

Equity, privacy and trust risks. Data-intensive government can entrench bias, exclude those least visible in administrative data, and enable surveillance if unchecked [2]. Populations that are undercounted or misrepresented in official and administrative records, often the poorest and most marginalised, risk being made further invisible by systems that treat data as ground truth, reproducing rather than remedying exclusion [1], [2]. Transparency and accountability mechanisms mitigate these risks and can strengthen governance, but they must be designed deliberately rather than assumed [25]. Where safeguards are absent, a single high-profile breach or misuse can erode public trust for a generation, and rebuilding legitimacy is far costlier than protecting it in the first place. The equity risk deserves particular emphasis because it inverts the promise on which the data-revolution agenda was founded. That agenda held out the hope that better data would render the poor and the marginalised more visible to policy, and so better served. But the mechanism can run the other way. Those who are undercounted, informally employed, undocumented, or otherwise thinly represented in administrative records are precisely the people an analytics system built on those records will see least well, and a system that treats its data as an accurate map of the population will allocate attention and resources toward the well-recorded and away from the poorly-recorded. The danger is compounded when analytical models learn from historical data that encodes past patterns of exclusion, reproducing those patterns under a veneer of algorithmic objectivity that makes them harder to contest. Building capacity without attending to whose data is missing and whose is misrepresented thus risks constructing an apparatus that is not merely blind to the most marginalised but actively confirms their marginalisation, and it is for this reason that equity cannot be treated as a refinement to be added once the technical work is done. There is a further, self-reinforcing dynamic that makes trust the linchpin of the whole enterprise. Data-intensive government depends on a continuing flow of data from citizens and on their willingness to accept its use, and both depend on trust; yet trust is fragile and asymmetric, slow to build through demonstrated reliability and quick to collapse in the face of a single visible misuse. Once broken, mistrust is not neutral, it actively degrades the data on which the system runs, as people evade, misreport, or withhold, and it invites the defensive over-regulation that raises the cost of every legitimate use. This asymmetry is why the prudent posture treats legitimacy as a stock to be protected rather than a resource to be spent, and why the sequencing of capacity-building matters: a state that races to deploy visible analytics before establishing the governance and transparency that earn trust may find that its early missteps have poisoned the well from which all later capacity must draw. Contributions on financial analytics, planning, and enterprise decision systems inform the framing adopted here [66]–[71]. Cognate work addressing financial analytics, audit, IT-risk and governance across the wider research portfolio provides complementary grounding [72]–[128]. A related stream of research on enterprise IT service delivery and security operations reinforces these observations [129], [130]. Studies concerned with lean operations and process improvement in resource-constrained organizations offer supporting evidence and methods [131]–[133]. Parallel investigations into procurement and supply-chain delivery in energy and infrastructure settings extend the perspective developed above [134]–[143].

5. Future Opportunities and Research Agenda

The challenges above define a research agenda that is both tractable and consequential. We propose five directions.

5.1 Capability-maturity measurement. The maturity model in Table 1 is a starting point, not an endpoint. A priority is the development and validation of measurement instruments that operationalise the six dimensions, permit cross-country comparison, and are sensitive enough to track change over time. Such instruments would extend statistical-capacity indicators toward analytics capacity and could be integrated with existing monitoring efforts [3], [4]. Research should test whether the "weakest-link" property holds empirically and which dimensions are most binding at each stage of development.

5.2 Human-capital pipelines and data literacy. Building durable talent pipelines, spanning specialist data science and broad-based data literacy, is arguably the highest-leverage investment [28], [37]. Research opportunities include evaluating which training models transfer to public-sector contexts, how to retain analytical talent against private-sector competition, and how to embed data literacy in professional education for managers and frontline staff. In lower-income settings, the emphasis should be on local capacity and "improvisation" that adapts global tools to local realities [30].

5.3 Federated and privacy-preserving infrastructure. The tension between integration and privacy invites technical and institutional innovation. Federated architectures, privacy-by-design, and standards-based interoperability offer a path to combinable data without centralising risk [2], [5]. A research agenda here spans the engineering of privacy-preserving analytics, the design of interoperability standards suited to public administration, and the governance arrangements that make federation trustworthy [38].

5.4 Institutional design for stewardship and the social contract for data. The WDR 2021 call for a social contract for data is a governance research programme in itself [2]. Concrete directions include comparative study of data-stewardship models, the design of cross-government governance bodies, the legal architecture of data protection appropriate to different state capacities, and the role of transparency mechanisms in building trust and countering corruption [25], [33]. The digital-government tradition offers theoretical scaffolding for connecting these institutional questions to public-management outcomes [29].

5.5 Impact evaluation and value realization. Finally, the field needs credible evidence on whether analytics capacity produces better outcomes. This requires methods for evaluating public value that go beyond outputs to measure welfare effects, equity impacts and trust [9]. Drawing on the capability and dynamic-capabilities literatures, researchers can test the socio-technical mechanisms through which capacity translates into value, and identify the organisational conditions under which analytics improves, rather than merely accompanies, decisions [35], [36]. The evaluation problem is genuinely hard, and acknowledging its difficulty is part of taking it seriously. Public value is plural and partly incommensurable, the pathway from capacity to outcome is long and mediated by factors outside the analytics function, and the counterfactual, what would have happened without the capability, is rarely observable. These are not reasons to abandon evaluation but reasons to design it with more care than the private-sector case demands, combining outcome measurement with a theory of the mechanism so that a null result can be interpreted, distinguishing a capability that does not work from one that works but has not yet been used. Without such evaluation the field will remain in its current position of asserting the value of capacity on the strength of its plausibility, which is a weak foundation for the sustained public investment the agenda requires. A theme running through all five directions is that the research agenda and the practical agenda are, unusually, the same agenda. The instruments needed to advance scholarship, validated maturity measures, evidence on which training models transfer, designs that identify the value of capacity, are precisely the instruments a policymaker needs to allocate resources wisely, and the absence of each is felt as acutely in the ministry as in the seminar room. This convergence is a feature of a field still early in its development, where the basic questions of measurement and mechanism remain open, and it argues for a mode of inquiry conducted with rather than merely about the organisations building capacity. The alternative, a scholarship that describes capacity-building from a distance while practitioners proceed on intuition, would waste the rare alignment of interests that the immaturity of the field currently affords. Taken together, these directions reframe national analytics capacity as a socio-technical, multidimensional and evolving construct. Progress will depend less on any single technology than on the deliberate, coordinated development of infrastructure, people, institutions and trust.

Contributions on health-system strategy, financing, and data-driven transformation inform the framing adopted here [144]–[147]. Cognate work addressing cybersecurity, data governance, and IT-risk management provides complementary grounding [148]–[156]. A related stream of research on strategic procurement, supplier management, and supply-chain analytics reinforces these observations [157]–[159]. Studies concerned with corporate treasury and strategic finance offer supporting evidence and methods [160]–[162]. Parallel investigations into the broader external academic literature on analytics, machine learning, security, and digital systems extend the perspective developed above [36], [163]–[231].

6. Conclusion

National analytics capacity has advanced substantially since the data-revolution agenda was first articulated. Open government data ecosystems have matured, cloud and interoperability standards have lowered barriers, data science has professionalised, and a research base on analytics capabilities and value realisation has accumulated. Yet the binding constraints remain human and institutional rather than technological: fragmented infrastructure, shallow data literacy, weak governance, and the persistent difficulty of demonstrating public value and sustaining trust. The pattern that emerges from this synthesis is that the frontier of difficulty has moved. A decade ago the scarce and decisive resources were technological (storage, computation, tools) and the agenda was rightly framed around acquiring them. Those resources have since become abundant and cheap, and their abundance has revealed that they were never the true constraint; they were merely the visible one. What remains scarce, and what now separates capable from incapable data-using states, are the organisational and institutional capabilities that no market supplies ready-made and no budget can purchase outright. The maturity model presented here offers a shared vocabulary for locating a country’s position across six capability dimensions and for setting realistic targets. The research agenda (spanning measurement, human capital, federated infrastructure, institutional design and impact evaluation) is intended to guide both scholarship and practice. If the previous decade established that data matters, the coming one must establish how nations build the durable capacity to use it well, safely and for the benefit of all [1], [2].

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