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BEYOND THE NUMBERS

Turning HR Metrics into Organizational Performance

Evidence, a results chain and responsible AI for Africa's public service

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Executive Summary

Public institutions across Africa now collect more workforce data than at any time in their history. Tanzania alone has registered 97.6 per cent of its public servants in a performance management information system, assessed staffing needs institution by institution and paid TZS 5.5 trillion in salaries through a single payroll system in nine months. This paper asks a practical question of all that data: what do public institutions gain from HR figures if those figures do not change decisions or improve services?

The paper argues that the central challenge is no longer a shortage of HR data. It is the weak conversion of data into insight, decisions, action and demonstrable results. It proposes a seven-link results chain (Activity, Metric, Insight, Decision, Action, Result, Impact) and tests it against three kinds of evidence: the international literature on people analytics, public-sector performance management and responsible AI; Tanzania's own official workforce statistics; and an exploratory questionnaire answered by 22 practitioners in October 2026.

The official statistics show that Tanzania already runs metric to decision chains at national scale. A staffing needs assessment found 655,737 staff in post against a requirement of 930,423, a gap of 274,686, and recruitment permits for 41,500 new posts followed in 2025/26. The 2016 to 2017 payroll verification removed more than 19,700 ghost workers at an estimated saving of TZS 238 billion a year. In each case the chain is strong at the front and thin at the back: the published record rarely shows whether the decision changed a service. Service Delivery Indicators explain why that matters. In 2014, 47 per cent of Tanzanian primary teachers were not in class during unannounced visits even though only 15 per cent were absent from school, and rural areas held just 9 per cent of the country's doctors. Headcount metrics count people; service outcomes depend on where they are and what they do.

The questionnaire shows how practitioners experience the same gap. Eight of 22 respondents placed their organisation at a reporting stage, three at monitoring, six at decision making and five at performance management. The most selected barriers were a lack of HR analytics skills and weak links between HR and strategy (14 each), ahead of fragmented systems and poor data quality (9 each). Respondents saw the most promise for AI in skills gap analysis (17) and workforce forecasting (16), named data privacy (16) and cybersecurity (12) as the main risks, and revealed a governance gap: 20 wanted clear policies before AI is scaled and 19 wanted human review of AI outputs, but only 10 believed their organisation's safeguards were adequate. These figures describe the respondents only; the sample is small and self selected.

The international evidence supports investing in people management while cautioning against overclaiming. Meta analyses find modest, positive associations between high performance HR practices and organisational performance (a corrected correlation of about .20 across 92 studies), training reliably changes knowledge but behaviour change depends on the work environment, and turnover harms performance most where it strikes customer facing and quality critical roles. Adoption of AI in HR is outrunning capability: the share of organisations piloting or using generative AI in HR rose from 19 to 61 per cent between 2023 and 2025, while only 8 per cent of HR leaders believed their managers could use it effectively.

The paper recommends ten actions, none of the first six requiring new technology: start with a decision rather than a dashboard; pair every priority HR metric with the service indicator it is meant to move; strengthen data quality and interoperability within the Personal Data Protection Act, 2022; build practical

analytical capability across HR, planning and M&E; institute a regular evidence to action meeting that records decisions and follow-up; evaluate important interventions proportionately; govern AI before scaling it, starting with aggregate, lower risk uses; protect employee trust and dignity; make learning part of performance management; and link workforce evidence to national performance reporting. A 90 day cycle and a 12 month horizon show how to begin.

Measure what matters. Understand what it means. Act on the evidence. Then check whether it worked.

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Abstract

Public institutions routinely report workforce figures on staffing, recruitment, training, turnover, absenteeism and performance appraisal. These measures matter, but their value is limited when they are reported without explaining what they mean for institutional performance or what managers should do next. This paper argues that the central challenge is not a shortage of human resource (HR) data; it is the weak conversion of data into insight, decisions, action and demonstrable results. Drawing on literature on people analytics, public sector performance management, evidence informed decision making and responsible artificial intelligence (AI), the paper proposes a practical results chain: Activity, Metric, Insight, Decision, Action, Result, Impact. It applies the chain to Tanzania's official workforce statistics, which show 97.6 per cent of public servants registered in a performance management system, a measured staffing gap of 274,686 against a requirement of 930,423, and a payroll verification that removed more than 19,700 ghost workers, but little published evidence on the service results of these decisions. It also presents an exploratory assessment of 22 practitioner responses collected in October 2026, predominantly from Tanzanian ministries. Eight respondents (36.4 per cent) placed their organisation at a reporting-focused stage, three (13.6 per cent) at monitoring, six (27.3 per cent) at decision-making and five (22.7 per cent) at performance management. The most selected barriers were limited HR analytics skills and weak links between HR and strategy (14 of 22 each). Respondents saw AI value in skills-gap analysis (17) and workforce forecasting (16), named data privacy (16) and cybersecurity (12) as the main risks, and 20 of 22 wanted clear policies before AI is scaled while only 10 judged their current safeguards adequate. The findings are illustrative, not representative, and do not establish causal effects. The paper offers a framework for linking workforce indicators to service-delivery outcomes, with recommendations on indicator design, analytical capability, leadership routines, data governance and human oversight of AI. Its central message is: measure what matters, understand what it means, act on the evidence and check whether it worked.

Keywords: *human resource management; people analytics; monitoring and evaluation; organisational performance; public service; artificial intelligence; Tanzania.*

1. Introduction: The Question Behind the Numbers

1.1 The question

In public institutions, HR reports arrive on time and in familiar formats. They show how many staff are in post, how many vacancies remain, how many employees attended training, how many appraisals were completed and how many employees left or were absent. These figures are not trivial. They establish the size and shape of the workforce and can reveal issues that require attention. Yet a report can be complete, accurate and well presented without answering the question that matters most to a head of institution: *so what?*

If training completion rises from 60 to 90 per cent, has staff capability improved? If vacancies fall, are services delivered more quickly or more equitably? If absenteeism increases, is the cause workload, poor supervision, health and safety, transport, morale or inaccurate recording? A metric describes a condition. By itself it rarely explains the condition or identifies the most appropriate response.

The distinction is particularly important in the public service. Workforce management is not an exercise in administering personnel processes. Its purpose is to ensure that institutions have the right people, skills, deployment, leadership and working conditions to implement policy and deliver services to citizens. The OECD's work on public employment emphasises strategic workforce planning, skills development and the capacity of public services to adapt to changing demands (OECD, 2023). The United Nations E-Government Survey notes that digital transformation depends on more than technology: leadership, data governance, digital literacy and robust infrastructure are enabling conditions (United Nations Department of Economic and Social Affairs, 2024).

1.2 Why now: the AI moment and Africa's public service

The conference theme asks how artificial intelligence can transform human capital management in Africa's public service. The question is timely. The African Union's Executive Council endorsed a Continental Artificial Intelligence Strategy at its 45th Ordinary Session in Accra on 18 and 19 July 2024 (African Union, 2024). Kenya launched a national AI strategy in 2025 and Rwanda adopted a national AI policy in 2023. In private-sector HR, the share of organisations piloting or implementing generative AI rose from 19 per cent in June 2023 to 61 per cent in January 2025 (Gartner, 2025b), and the Society for Human Resource Management (SHRM, 2024, 2025) reports that the share of organisations using AI for HR activities rose from 26 per cent in 2024 to 43 per cent in 2025.

Enthusiasm has outpaced readiness. Only 8 per cent of HR leaders surveyed by Gartner in 2025 believed their managers had the skills to use AI effectively (Gartner, 2025a). The International Labour Organization estimates that in low income countries only 0.4 per cent of employment is exposed to automation by generative AI, while 10.4 per cent is exposed to augmentation; clerical work, which includes much of HR administration, is the most exposed occupational group (Gmyrek et al., 2023). For African public HR functions, the realistic near-term effect of AI is therefore to augment analysis, not to replace staff. That makes the quality of the underlying data and the capacity of managers to interpret analysis more important, not less. A model trained on incomplete or biased records will produce confident errors at scale, as Amazon discovered when its experimental recruiting tool learned to penalise résumés that mentioned women (Dastin, 2018).

The APS-HRMNET community has already recognised the direction of travel. At its 8th conference in Nairobi in November 2023, delegates resolved to develop skills in metrics and data analytics and to strengthen HR planning (Samilu, 2023). The 11th conference in Zanzibar, which expects more than 800 delegates from across the continent, places AI at the centre of that agenda (Daily News, 2026). This paper takes that resolution as its starting point and asks what it would mean in practice.

1.3 Tanzania as a case

Tanzania offers an instructive case because its investment in workforce data systems has been rapid and extensive. Between July 2023 and March 2024, 589,076 of 603,699 public servants (97.6 per cent) were registered in the Public Employees Performance Management Information System and 571,586 (94.7 per cent) had entered performance plans (President's Office, Public Service Management and Good Governance [PO-PSMGG], 2024, p. 35). A national staffing needs assessment covering 553 of 571 public institutions found 655,737 staff in post against a requirement of 930,423, a shortage of 274,686 (PO-PSMGG, 2026, para. 40(xii)). The 2025/26 budget allocated TZS 13.17 trillion to public servants' salaries, about 23 per cent of total expenditure (Ministry of Finance, 2025, p. 4). Few African public services have more complete workforce data. The question of what the data are used for is therefore unusually sharp. It is also a question the country has set itself: Tanzania Development Vision 2050, launched in July 2025, states that "the quality of public service is at the heart of effective governance", acknowledges that recruitment processes have often lacked transparency and merit based principles, records the introduction of performance based management systems, and devotes a section to evidence driven implementation and accountability (National Planning Commission, 2025, pp. 17, 62).

1.4 Objectives and structure

The paper approaches HR measurement through a monitoring and evaluation (M&E) lens and asks how public institutions can move from reporting HR metrics to using them as evidence for better management decisions and improved organisational performance. It has four objectives: to distinguish HR reporting from HR analytics and performance evidence; to introduce a practical results chain for translating metrics into action; to present exploratory findings from Tanzania's official statistics and a small practitioner assessment; and to propose steps that public institutions can take to strengthen the contribution of HR data, including the responsible use of AI.

Section 2 reviews the literature and sets out the conceptual framework. Section 3 describes the methodology. Section 4 reads Tanzania's official workforce statistics through the results chain. Section 5 reports the practitioner assessment. Section 6 discusses how to make the "so what?" question routine, with worked examples. Sections 7 and 8 offer recommendations and an implementation roadmap. Section 9 states limitations and a research agenda, and Section 10 concludes.

2. Conceptual Framework and Literature Review

2.1 From HR metrics to people analytics

HR metrics are measures of workforce characteristics or HR processes: vacancy rates, time to recruit, training participation, turnover and appraisal completion. People analytics goes further. The Chartered Institute of Personnel and Development (CIPD, 2025) defines it as "analysing data about people to solve business problems". Marler and Boudreau (2017, p. 15) define HR analytics as an HR practice enabled by

information technology that uses descriptive, visual and statistical analyses of data on HR processes, human capital, organisational performance and external benchmarks to establish business impact and enable data-driven decision-making. The difference between the two definitions and a conventional HR report lies in the words "problems", "impact" and "decision-making". Analytics begins with a question and ends with a choice.

The distinction is not between having data and having none. It is between describing activity and investigating what the activity means. A training dashboard reports the number of staff trained. An analytical question asks whether the training addressed a verified skills gap, whether participants applied what they learned and whether work quality or service performance subsequently changed. Boudreau and Ramstad (2007) formalise this in the LAMP framework: measures without logic, analytics and a process for acting on them produce reports, not decisions. Becker et al. (2001) make the same argument with the HR scorecard, which links HR deliverables to strategy in the manner of Kaplan and Norton's (1992) balanced scorecard. Fitz-enz (2010) and Edwards and Edwards (2019) extend the argument to predictive analytics, and Levenson (2018) shows that workforce analytics adds value when it is tied to strategy execution rather than run as a technical exercise.

The academic evidence base calls for ambition and caution in equal measure. Marler and Boudreau's (2017) review found only 14 peer-reviewed articles on HR analytics in leading journals between 2005 and 2016. Tursunbayeva et al. (2018), reviewing 58 articles, concluded that published evidence of outcomes "remains sparse" and that consideration of ethical issues was "largely absent". Angrave et al. (2016) warned that HR was "set to fail the big data challenge" because the function lacked the analytical capability and strategic positioning to use data well. Minbaeva (2018) argues that credible human capital analytics rests on three dimensions, data quality, analytical competencies and the strategic ability to act, at three levels, individuals, processes and structures. Rasmussen and Ulrich (2015) show from practice that analytics avoids becoming a management fad only when it starts from a business problem rather than from the data. The implication is not that analytics has no value. It is that institutions should not assume that buying a system or producing more dashboards will automatically improve results.

2.2 Adoption and maturity: what the global surveys show

Surveys of large organisations document a persistent gap between aspiration and capability. In 2017, 71 per cent of companies surveyed by Deloitte saw people analytics as a high priority, but only 8 per cent reported having usable data, only 9 per cent believed they understood which talent dimensions drive performance and only 15 per cent had broadly deployed HR and talent scorecards for line managers (Fineman, 2017). A year later 84 per cent viewed people analytics as important or very important, yet only 10 per cent considered themselves very ready to manage the data protection risks involved (Schwartz et al., 2018). The CIPD's 2018 survey of 3,852 professionals found that 71 per cent of HR respondents had access to people data but only 52 per cent said their organisation used it to solve business problems; just 21 per cent of UK HR professionals were confident in advanced analytics, against 46 per cent in South-East Asia, and 6 per cent used advanced techniques daily (CIPD, 2018).

More recent studies suggest that teams are growing faster than impact. Insight222's 2024 survey of 348 companies found people analytics teams growing or stable in 90 per cent of companies, but only 10 per cent qualified as "A teams" with demonstrated strategic influence while 57 per cent were "D teams"; 41 per cent had measured improved business performance from analytics (Ferrar et al., 2024). The 2025/26 edition

of 372 organisations reports that 52 per cent had measured business improvements, rising to 90 per cent among the strongest teams, and that 70 per cent had invested in AI (Insight222, 2026). On AI specifically, SHRM's survey of 2,366 HR professionals found 26 per cent of organisations using AI for HR activities in January 2024, with recruiting the most common use among adopters (64 per cent), rising to 43 per cent of organisations in 2025 (SHRM, 2024, 2025). Gartner's panel of HR leaders moved from 19 per cent piloting or implementing generative AI in June 2023 to 38 per cent in January 2024 and 61 per cent in January 2025 (Gartner, 2024, 2025b). McKinsey's 2025 global survey found that only half of respondents who used generative AI in HR reported that it had reduced costs (McKinsey & Company, 2025). The World Economic Forum expects 39 per cent of workers' existing skills to be transformed or become outdated by 2030 and estimates that 59 of every 100 workers will need training by then; 85 per cent of employers plan to prioritise upskilling (World Economic Forum, 2025).

Three lessons follow for African public institutions. Maturity is scarce even where resources are abundant, so a public institution at the reporting stage is in large company. The binding constraints are capability, strategic positioning and governance rather than software. And the organisations that report measurable gains are those that tie analytics to specific decisions. These are the same three themes that the practitioner questionnaire in Section 5 surfaces.

2.3 Does people management affect performance? The meta-analytic evidence

Any argument for investing in HR analytics rests on a prior claim: that people management practices influence organisational performance. The evidence for that claim is extensive and, read carefully, supportive but modest. Table 1 summarises the main meta-analyses.

Table 1. Meta analytic and large sample evidence linking people management to organisational outcomes

Study	Scope	Headline finding	Implication for public HR analytics
Combs et al. (2006)	92 studies; 19,319 organisations	Corrected correlation of .20 between high-performance work practices and performance; .28 for systems of practices against .14 for single practices	Bundles of practices matter more than isolated interventions
Saridakis et al. (2017)	8 longitudinal studies; 1,661 organisations	Corrected correlation of .287 between HPWPs and subsequent performance; longitudinal data "only allow researchers to suggest a possible causal inference"	Even time-ordered data warrant modest causal language
Jiang et al. (2012)	Meta-analysis using the ability-motivation-opportunity model	Skill, motivation and opportunity-enhancing practices affect financial outcomes directly and through human capital, motivation, turnover and operational outcomes	The mechanism runs through people and operations; measure the intermediate links
Huselid (1995)	968 US firms	One standard deviation more HPWPs associated with 7.05% lower turnover and US$27,044 more sales per employee	Workforce practices have measurable economic value
Harter et al. (2002)	7,939 business units in 36 companies	Generalisable relationships between engagement and customer satisfaction, productivity, profit, turnover and accidents	Engagement data are worth collecting if acted upon

Study	Scope	Headline finding	Implication for public HR analytics
Harter et al. (2024)	736 studies; 183,806 units; 3.35 million employees; 90 countries	Top against bottom-quartile engagement: 78% lower absenteeism, 18% higher sales productivity, 23% higher profitability, 63% fewer safety incidents	Engagement differences are large at the unit level, where managers act
Arthur et al. (2003)	162 sources; 397 effect sizes	Training effect sizes of about d = 0.62 for reaction, learning, behaviour and results criteria	Training works, on average; the question is whether it transfers
Blume et al. (2010)	89 studies	Transfer of training depends on cognitive ability, conscientiousness, motivation and a supportive work environment; stronger for open skills such as leadership	Training completion predicts little without a supportive workplace
Hancock et al. (2013)	48 samples; N = 24,943	Turnover and performance correlate at −.03 overall, 10 for customer service and .12 for quality and safety outcomes	Aggregate turnover hides where losses hurt
Park and Shaw (2013)	110 independent correlations; N = 120,066	Total turnover and performance correlate at ρ = −.15; voluntary −.15; reductions in force −.17; involuntary −.01	Who leaves matters more than how many
Boushey and Glynn (2012)	30 case studies from 11 papers	Median cost of replacing an employee of 21% of annual salary (excluding executives and physicians)	Retention in critical roles has a calculable value
McCartney and Fu (2022)	155 Irish organisations	HR analytics affects performance through evidence-based management (indirect effect 0.16); HR technology is an antecedent, not the mechanism	Analytics pays off only when managers use evidence in decisions

Note. Effect sizes are correlations unless stated. All are associations observed mainly in private-sector settings; see Section 2.4 for the public-sector qualification.

Three features of this evidence shape the framework. The effects are real but modest: a correlation of .20 to .29 means that people management explains a minority of the variance in performance, with strategy, funding, demand and technology explaining the rest. The effects run through intermediate outcomes, human capital, motivation, turnover and operational performance, which is why a results chain with explicit intermediate links is more informative than a direct line from HR activity to institutional outcome. And the effects are strongest for bundles of practices and for specific, critical groups of staff, which is why disaggregation matters more than aggregate reporting. Fernandez and Gallardo-Gallardo (2021), reviewing 64 studies, identified 14 barriers to HR analytics adoption in four categories: data and models, software and technology, people, and management. The practitioner questionnaire in Section 5 finds the same four categories, in the same order of difficulty.

2.4 Theoretical foundations and the public-sector qualification

The resource-based view and human capital. The resource-based view holds that organisational resources contribute to sustained performance when they are valuable and difficult to imitate (Barney, 1991). Human capital, the knowledge, skills and experience of employees, is one such resource, but its value depends on how it is organised and applied. For a public institution, having qualified staff on the payroll is not the same as having the capability to deliver a service. Capability also depends on deployment,

tools, managerial support, organisational routines and the authority to act. HR analytics is most useful when it shows not only who is employed but whether workforce capabilities are available where institutional priorities require them.

The ability motivation opportunity perspective. The AMO framework proposes that performance depends on employees' ability to do the work, their motivation to apply that ability and their opportunity to contribute (Appelbaum et al., 2000; Boxall & Purcell, 2016). Jiang et al. (2012) show meta-analytically that skill-enhancing practices build human capital while motivation- and opportunity-enhancing practices work mainly through motivation. The framework is a corrective to explanations that treat every performance problem as a skills deficit. Training may improve ability, but it will not improve results if employees lack equipment, clear procedures, supportive supervision or discretion to solve problems. Low output should not automatically be read as low effort. HR indicators need to be read alongside working conditions and operational constraints.

Public value and institutional purpose. Private-sector analytics focuses on productivity, cost, retention or profitability. Public institutions must also consider legality, equity, accessibility, accountability and public trust. Moore's (1995) public value perspective holds that performance should be understood in relation to the value an institution creates for the public, the legitimacy and support it maintains and its operational capacity. An HR intervention should therefore not be judged only by whether it reduces costs. It may be valuable if it improves service access for remote communities, reduces avoidable errors, protects impartiality or strengthens continuity in a critical service.

Why the public sector is different. Knies et al. (2024) argue that strategic HRM research cannot simply transfer private-sector findings to public organisations, for three reasons: public performance is multidimensional because institutions pursue multiple and often conflicting goals; public employers rely more on ability- and opportunity-enhancing practices than on financial incentives, and their HR decisions are constrained by politicians and collective bargaining; and the mechanisms differ, with red tape limiting managers' room to act and public service motivation central. The empirical public-sector work supports the general proposition while confirming the qualification. Gould-Williams (2003) found in UK local government that HR practices were strong predictors of workplace trust and perceived organisational performance. Vermeeren et al. (2014), analysing 6,253 Dutch municipal employees, found that job satisfaction mediates the link between HRM and performance and that a stimulating leadership style increases the HR practices actually used. Mostafa et al. (2015), surveying 671 professionals in Egyptian health and higher education, found that public service motivation partially mediates the effect of high-performance HR practices on commitment and citizenship behaviour. Boselie et al. (2021) nevertheless conclude from a review of 2000 to 2016 that cross-fertilisation between HRM and public administration research remains limited, which leaves public managers with fewer context-specific findings than they need.

2.5 An M&E lens: results chains, contribution and attribution

Monitoring and evaluation offers a useful discipline for HR analytics because it asks how resources and activities are expected to produce outputs, outcomes and longer term effects. Kusek and Rist's (2004) ten-step model for results based M&E systems begins with a readiness assessment and ends with sustaining the system in the organisation, and insists that indicators be chosen for the outcomes they track rather than for the ease of collecting them. The OECD Development Assistance Committee's revised evaluation criteria of

relevance, coherence, effectiveness, efficiency, impact and sustainability (OECD/DAC Network on Development Evaluation, 2019) give managers a vocabulary for asking whether an HR intervention was the right one, whether it worked and whether its effects will last.

The results chain proposed in this paper is Activity, Metric, Insight, Decision, Action, Result, Impact. Activity is what the institution does; the metric is the indicator used to observe it; insight is the explanation developed from the evidence; decision is the management choice; action is the intervention implemented; result is the observed change; and impact is the wider contribution to public value. The chain differs from a standard logframe in two ways. It inserts "insight" and "decision" between the metric and the action, because that is where HR reporting most often stops. And it treats the result as something to be checked, not assumed.

Evaluation thinking is especially important when leaders ask whether an observed improvement was caused by an HR intervention. Before and after changes are useful but do not prove causation; changes in funding, demand, technology, leadership, policy or external conditions may also influence performance. The CIPD (2025) distinguishes correlation from causation and notes that establishing causation usually requires stronger analysis, including data across time. Mayne's (2001, 2012) contribution analysis offers a practical middle path: rather than attempting to attribute an outcome to one intervention, the manager builds a plausible account of how the intervention contributed, tests the account against the evidence and the alternative explanations, and states the confidence warranted. Institutions should make claims proportionate to the evidence available.

2.6 Performance measurement: useful indicators and the danger of targets

Measurement is a means, not the objective. Performance indicators make complex work visible, but every indicator is a partial representation of reality. Bevan and Hood (2006) show how target driven systems in the English National Health Service produced gaming and unintended consequences when organisations focused on the measure rather than the purpose. Hood (2006) distinguishes three forms of gaming: ratchet effects, where managers understate capacity to secure easier future targets; threshold effects, where effort concentrates on units just below the target while others are neglected; and output distortion, where the reported number is manipulated. Kelman and Friedman (2009) offer the counterweight: their examination of the four-hour emergency-department target found real improvement and little evidence of dysfunction, which suggests that well-designed targets with credible monitoring can work.

In HR, a target to reduce recruitment time may encourage speed at the expense of assessment quality; a target for training numbers may reward attendance rather than learning; and a target for appraisal completion may produce forms completed without meaningful feedback. Tanzania's 94.7 per cent plan-completion rate in PEPMIS is a reminder of the last risk. These are not arguments against targets. They are reasons to combine indicators, review their consequences and retain professional judgement. Behn (2003) lists eight purposes of performance measurement: to evaluate, control, budget, motivate, promote, celebrate, learn and improve, and shows that no single measure serves all eight. An institution should know which purpose each HR indicator serves.

Two practical rules follow. Use balanced measures: recruitment should be judged not only by days to fill a vacancy but by applicant quality, fairness, retention after appointment, cost and service impact; training by participation, demonstrated competence, application at work and a related service-quality measure. And define indicators consistently: a vacancy rate is meaningless if one unit counts approved posts, another

funded posts and a third only advertised posts. Before comparing institutions, leaders should agree the numerator, denominator, reference date, exclusions and data source, document them in a data dictionary and change them transparently. The revision of Tanzania's national staffing gap from 441,366 to 274,686 between 2024 and 2026, discussed in Section 4, shows how much a headline figure can move when the definition of "requirement" is refined.

2.7 Why managers use, or do not use, performance information

The availability of data does not guarantee its use. Moynihan and Pandey (2010) asked why public managers use performance information and found that public service motivation, the manager's leadership role, the availability of information, organisational culture and administrative flexibility explain much of the variation. Kroll's (2015) systematic review of the empirical literature identifies the drivers consistently found: a mature measurement system, leadership support, support capacity, an innovative culture and goal clarity. Head (2016) places evidence informed practice in a complex environment in which research evidence interacts with professional experience, stakeholder knowledge and political judgement. Rousseau (2006) argues that evidence-based management requires managers to combine the best available research with organisational facts and practitioner judgement, and Cairney (2016) reminds policy actors that evidence competes with values and institutions for attention. In the public service this is especially relevant: a statistical pattern may identify a problem, while frontline employees explain why it occurs and citizens describe how it affects them.

A reporting loop ends when a report is submitted. A learning loop starts with a question, tests possible explanations, takes action and checks whether the action worked. This is Argyris and Schön's (1978) distinction between single-loop learning, which corrects errors within existing assumptions, and double-loop learning, which questions the assumptions themselves. If an HR report identifies high turnover in a specialised unit, the next step is not automatically a retention allowance. Managers might examine exit reasons, workload, career progression, supervisory practice, location and labour-market competition. The response should follow the diagnosis, not precede it, and a subsequent review should establish whether the chosen response improved retention without creating unfairness elsewhere.

Honest reporting depends on psychological safety. Staff may be reluctant to report poor data or disappointing results if they expect blame, yet a system that punishes every adverse finding encourages concealment and superficial compliance. Edmondson's (1999) research on learning behaviour in work teams, and her later synthesis (Edmondson, 2019), show that teams in which people can raise concerns and admit errors learn faster and perform better. For HR analytics this means that data-quality problems should be corrected rather than hidden, unexpected results investigated, and honest learning distinguished from negligence or misconduct.

2.8 Government analytics, HRMIS and the African public-service context

Digital government is organisational change, not the conversion of paper forms into electronic ones. The United Nations E-Government Survey 2024 treats digital transformation as a broad public-sector capability and stresses institutional readiness alongside technological opportunity; Tanzania's E-Government Development Index of 0.4327 in 2024 placed it 153rd of 193 countries, close to the African average of 0.4247 and well below the world average of 0.6382 (United Nations Department of Economic and Social Affairs, 2024). The OECD's Recommendation on Public Service Leadership and Capability calls for

evidence informed workforce planning based on the skills needed and available, while protecting personal data (OECD, 2019). The World Bank's Government Analytics Handbook argues that the personnel, payroll and performance records governments already hold are an underused resource for improving public administration (Rogger & Schuster, 2023). Its chapter on HR and payroll data notes that public-sector wages represent around one fifth of total government spending according to the IMF and roughly a quarter of general government expenditure according to World Bank estimates, and shows how basic payroll and HRMIS statistics can help policy makers break down the causes of workforce problems and project the fiscal impact of reforms (Tavares et al., 2023). The World Bank's Worldwide Bureaucracy Indicators put Tanzania's wage bill at 23.6 per cent of public expenditure and 4.4 per cent of GDP in 2022, with the public sector accounting for 20.1 per cent of paid employment and public employees earning a premium of about 51 per cent over private employees in 2020 (World Bank, 2025).

Which management practices actually improve performance in developing country civil services? The most direct evidence comes from a survey of about 23,000 civil servants in ten countries, including Ghana, Malawi and Uganda, conducted for the UK Department for International Development. It found that formal performance evaluations can foster a performance orientation, but that where objectives are not set in advance and results do not affect careers or pay, evaluations have counterproductive effects; across the sample, only performance-oriented promotions were significantly associated with performance, and civil servants in most countries disagreed that performance influenced their pay (Meyer-Sahling et al., 2018). This finding has a direct bearing on Tanzania's 94.7 per cent plan-completion rate: an appraisal system that is complete but inconsequential may do less than nothing. The same research found that formally meritocratic practices such as written examinations and job advertisements reduce politicisation and nepotism in most of the countries studied, which supports the African Charter's commitments to merit-based recruitment (Article 19), performance management based on clear and measurable criteria (Article 20) and capacity development (Article 21) (African Union, 2011). Tanzania ratified the Charter in 2015.

African experience with HRMIS and payroll data shows both the value and the limits of the metric. Table 2 summarises verified figures from seven public services. Three patterns stand out. Every country that has reconciled its payroll against physically verified staff has found ghost workers in the thousands or tens of thousands, and every country that stopped reconciling has found them again: anti-corruption investigators in Nigeria were still identifying suspected ghost workers in 2026 after a decade of IPPIS (Blueprint, 2026). Vacancy rates against approved establishments are large almost everywhere, from 8.5 to 10.7 per cent in South Africa to 46 per cent in Uganda and about 30 per cent in Tanzania, which means that headcount-based planning is a problem across the continent, not a Tanzanian peculiarity. And where performance data are evaluated and published, as with Rwanda's district Imihigo contracts, the variation between units is wide enough (53 to 84.5 per cent in 2017/18) to make the data decision-relevant. The lesson for the results chain is that a payroll or establishment metric produces results only when it is used continuously and connected to a decision.

Table 2. Workforce data systems and verified figures in selected African public services

Country	System or exercise	Latest verified figure	Source
Tanzania	PEPMIS/PIPMIS (launched June 2024, now e-Utendaji); HCMIS payroll; e-Msawazo needs assessment	97.6% of public servants registered; 655,737 in post against 930,423 required (gap 29.5%)	PO-PSMGG (2024, 2026); Machira (2024)

Country	System or exercise	Latest verified figure	Source
Kenya	Biometric registration of public servants, September to October 2014 (CARPS)	160,012 of 172,522 on the payroll presented; salaries of 12,510 stopped	Business Daily (2014)
Ghana	SSNIT biometric headcount (2016); Auditor-General payroll audit, June 2018 to January 2020	26,589 names removed from April 2017; 7,823 ghost names costing GH¢467.6 million	Ghana News Agency (2017); Petetsi (2020)
Nigeria	Integrated Payroll and Personnel Information System (IPPIS)	37,395 ghost workers found by 2016; about 70,000 removed and over N220 billion saved by 2022; annual savings of N85 billion (2017) and N202 billion (2018); 720,000 federal public servants; suspected ghost workers still found in 2026	Gulf News (2016); Bloomberg (2019); The Eagle Online (2022); Blueprint (2026)
Uganda	Human Capital Management system (live 17 November 2021)	356,504 of 658,104 approved posts filled (54%); 301,600 vacant at 31 December 2024	Ministry of Public Service, Uganda (2021); Mugabi (2026)
Rwanda	Imihigo district performance contracts, evaluated annually since 2006	2017/18 average district score 73%; range 53% (Nyanza) to 84.5% (Rwamagana)	National Institute of Statistics of Rwanda (2018); Scher (2010)
South Africa	PERSAL personnel and salary system	About 1.2 million public servants; 102,153 vacant funded posts (8.5%) in January 2025; 10.74% in December 2025	Ensor (2025); Parliamentary Monitoring Group (2026)

Note. Figures are as reported by the sources named; definitions of "ghost worker" and "vacancy" differ between countries and years.

African public services operate across varied fiscal, institutional, linguistic and infrastructure conditions. A model developed in a well resourced organisation may assume complete digital records, stable job classifications and specialist analytical teams. Those assumptions do not hold everywhere. A responsible approach starts with the decision problem and the data that can be trusted, then builds capability incrementally. In one institution a validated spreadsheet and monthly review may be appropriate; in another, integrated workforce and service data may support forecasting. Maturity should be assessed by usefulness and governance, not by software sophistication. APS-HRMNET's own mandate points the same way: to professionalise HR management in the public service and to "provide and share tools, models, methods and data" (African Public Sector Human Resource Managers' Network, n.d.).

For Tanzania, the framework proposed here can be aligned with existing performance management, planning and M&E routines rather than creating a separate reporting burden. A ministry, region, local government authority or agency could select one service priority, identify the workforce factors plausibly influencing it and review a small number of linked measures with HR, planning, M&E, finance and operational managers. Section 4 shows that the data for such reviews already exist.

2.9 AI in HR: promise, risk and governance

AI may support workforce forecasting, skills-gap analysis, recruitment analytics, training-needs analysis and early identification of retention risks. These uses can help institutions process large datasets and identify patterns that manual reporting cannot. However, the quality of an AI-generated insight depends on the question asked, the data used, the model's design and the way the result is interpreted. The ILO's recent work cautions that AI in HR can reproduce flawed objectives, biased or incomplete data and opaque decision rules (Berg & Johnston, 2025), and earlier ILO analysis argues for a human-centred approach

attentive to workers' rights, voice and the conditions under which technology is deployed (Cappelli & Rogovsky, 2023). These concerns are most significant when systems inform recruitment, promotion, performance ratings, discipline or decisions that affect a person's livelihood.

Regulators have reached the same conclusion. The European Union's AI Act classifies as high-risk any AI system used for the recruitment or selection of natural persons, for decisions affecting the terms of work relationships, promotion or termination, for task allocation based on behaviour or personal traits, and for monitoring and evaluating the performance and behaviour of workers (Regulation (EU) 2024/1689, Annex III, point 4). The classification carries obligations for risk management, data governance, transparency and human oversight, which a 2026 amendment made applicable to Annex III systems from 2 December 2027 (Regulation (EU) 2026/1744). The cases that prompted it are instructive. Amazon abandoned an experimental recruiting model after it learned to penalise résumés containing the word "women's" and to downgrade graduates of two all-women's colleges (Dastin, 2018). In *Mobley v. Workday, Inc.*, a United States federal court in May 2025 granted preliminary certification of a nationwide collective of applicants alleging age discrimination by an AI screening system, and in July 2025 extended it to applicants scored by a related tool; the rulings are procedural and make no finding of liability, but they establish that vendors of hiring algorithms can face claims directly (Mobley v. Workday, Inc., 2025).

Governance frameworks now exist to structure due diligence. The NIST AI Risk Management Framework organises the work around four functions: Govern, Map, Measure and Manage (National Institute of Standards and Technology, 2023). Applied to HR, Govern means assigning responsibility and policies; Map means understanding the context, affected groups and potential harms; Measure means testing performance, validity, privacy and bias; and Manage means responding to identified risks and monitoring the system after deployment. UNESCO's Recommendation on the Ethics of Artificial Intelligence places human rights and dignity at the centre and highlights privacy, fairness, transparency, accountability and human oversight (UNESCO, 2022). The OECD's AI Principles, updated in 2024, add inclusive growth, human-centred values, transparency, robustness and accountability (OECD, 2024), and ISO/IEC 42001:2023 provides an auditable management-system standard (International Organization for Standardization, 2023). Africa's own instruments are recent: the AU Continental AI Strategy (African Union, 2024), Rwanda's National AI Policy, approved in April 2023 with a priority area on trustworthy AI adoption in the public sector (Ministry of ICT and Innovation, 2023), and Kenya's National AI Strategy 2025 to 2030, launched in March 2025 (Ministry of Information, Communications and the Digital Economy, 2025). Tanzania has not yet adopted a national AI strategy: a draft National Artificial Intelligence Strategy Framework was circulated in July 2025 (Ministry of Communication and Information Technology, 2025), and UNESCO's readiness assessment for the country recommends finalising the strategy and establishing a multi-stakeholder National AI Council (UNESCO, 2025). In the meantime the Personal Data Protection Act, 2022, in force since 1 May 2023 with its collection, processing and complaints regulations of 2023, establishes the legal basis, the Personal Data Protection Commission and the obligations that any HR analytics or AI use must satisfy (Personal Data Protection Act, 2022; Msinjili et al., 2023). Public institutions in Tanzania therefore operate in a window in which the data-protection law applies but AI-specific guidance for the public service does not yet exist; the governance checklist in Section 7.2 is designed for that window.

Two principles follow for public HR. Do not confuse prediction with explanation: a model may predict that an employee is likely to leave, but prediction alone does not say why, and a prediction should trigger inquiry rather than an automatic penalty. And match safeguards to consequences: a workforce forecast used to plan

aggregate training is different from a model used to rank individuals for promotion, and the higher the consequence for a person, the stronger the evidence, safeguards, explanation and review process should be. AI cannot repair poor source data or substitute for leadership responsibility. Where evidence is weak, the appropriate output may be a request for better data, not a confident prediction.

2.10 What the literature does not settle

The evidence base is still developing. Marler and Boudreau (2017) identified limits in the empirical evidence linking HR analytics to performance, and Tursunbayeva et al. (2018) found outcome evidence sparse. The technology landscape has since changed rapidly, but the central evaluation challenge remains: adoption is not the same as effectiveness. Institutions need studies that report not only whether a tool was deployed, but whether its outputs were used, what decisions changed, what outcomes followed, which groups benefited or were harmed and what it cost to maintain the system.

Public-sector evidence needs context. Most people analytics research has emerged from business settings, while public institutions face distinct accountability requirements and multiple, sometimes competing, goals (Knies et al., 2024). A model that optimises speed may undermine fairness; one that reduces expenditure may weaken access; and one that ranks individuals may discourage collaboration. African public-sector evidence is thinner still: the paper found no published study that follows an HR analytics intervention in an African public institution from decision to service outcome. Section 4 shows that Tanzania has the data to produce such a study. Section 9 proposes how.

3. Methodology

3.1 Research design

The paper combines three sources of evidence. The first is a focused review of peer reviewed and policy literature on people analytics, public sector performance management, evidence informed management and responsible artificial intelligence (AI). The second is secondary analysis of official Tanzanian statistics on the public service workforce, drawn from budget speeches of the President's Office, Public Service Management and Good Governance (PO-PSMGG), the Ministry of Finance, parliamentary records, the Controller and Auditor General and the World Bank's Service Delivery Indicators and human resources for health assessments. The third is descriptive analysis of an exploratory practitioner questionnaire administered in October 2026. The design is deliberately pragmatic: it asks what the numbers that public institutions already hold can tell managers, and what practitioners say prevents them from acting on those numbers.

The official statistics are used in two ways. They describe the scale of the workforce information that Tanzania already produces, and they are read as worked examples of the results chain proposed in Section 2.5. Each official figure is cited to the document and paragraph in which it appears so that readers can verify it. Where a figure appears in more than one official source with different values, the paper states the discrepancy rather than selecting one silently. This transparency is itself part of the argument: a headline workforce metric depends on how its numerator and denominator are defined.

3.2 The practitioner questionnaire

The questionnaire covered organisational type, professional role and experience; HR metrics and reporting practices; the use of HR evidence in decisions; digital HR systems; barriers to analysis; potential uses and risks of AI; perceived HR data maturity; attitudes to AI governance; and examples of decisions informed by HR information. It was distributed electronically to HR, planning and monitoring and evaluation (M&E) practitioners in October 2026 and returned 22 complete records. Respondent usernames and email addresses were removed before analysis and no individual response is reported.

Twenty respondents worked in Tanzania, one in Kenya and one in Zimbabwe. Twelve worked in ministries and five in government parastatals or state-owned enterprises; the remainder came from local government, an executive agency and civil society. One organisational-category entry contained a person's name rather than an organisation type; it is treated as a dataquality limitation and is not reproduced. Table 5 summarises the profile.

The analysis uses simple counts and percentages. Multi select questions were counted once for each option selected, so percentages for those items do not sum to 100 chains already exist in the Tanzanian public service and where they stop short of demonstrated results. The questionnaire shows how practitioners experience those chains from the inside. Read together, the sources allow the paper to ask a sharper question than any one of them could support alone: given that the data infrastructure now exists and that practitioners want to use it, what specifically prevents workforce evidence from changing decisions and services?

4. What Tanzania's Own Numbers Already Show

Before turning to the questionnaire, it is worth examining the workforce metrics that the Tanzanian public service already produces. They demonstrate three things. The measurement infrastructure is now extensive. Several metric-to-decision chains are already operating at national scale. And in each case the chain is strongest at the front (activity, metric, decision) and weakest at the back (result, impact), which is precisely where the "so what?" question lives.

4.1 The measurement infrastructure

Tanzania has invested heavily in digital workforce records. The Public Employees Performance Management Information System (PEPMIS) and its institutional counterpart (PIPMIS) were rolled out from 2023 and formally launched, together with e-Watumishi, e-Mrejesho and the Human Resources Assessment system, by the Prime Minister on behalf of the President in Dodoma on 23 June 2024, replacing the paper-based Open Performance Review and Appraisal System (OPRAS) (Machira, 2024). Between July 2023 and March 2024, 570 public institutions were trained to implement the Public Employees Performance Management Information System (PEPMIS) and its counterpart for institutions (PIPMIS); 589,076 of 603,699 public servants, or 97.6 per cent, had been registered in the system; and 571,586, or 94.7 per cent, had entered individual performance plans (PO-PSMGG, 2024, p. 35). Over the same period, 433 employers used the HR and payroll information system to pay TZS 5.52 trillion in salaries and salary-related allowances, and 145,472 personnel and payroll records were processed in the payroll system (HCMIS) (PO-PSMGG, 2024, p. 35). The Watumishi Portal now lets staff apply for leave, transfers and loans, request duty-station swaps and view payslips without visiting an office (Nipashe, 2025).

By 2025/26 the performance system had been renamed e-Utendaji. PO-PSMGG reports that it monitored and analysed performance plans and performance contracts of 256 institutions through the system, supported 18,300 staff in 13 regional secretariats and 90 local government authorities through a "Mobile Clinic", and plans to extend support to all 571 public institutions (PO-PSMGG, 2026, paras 40(vi), 40(xxxv), 63(xxx)). The wage bill that these systems administer is substantial: the 2025/26 budget allocated TZS 13.17 trillion to public servants' salaries out of total expenditure of TZS 56.49 trillion, or about 23 per cent (Ministry of Finance, 2025, p. 4), a share consistent with the World Bank's estimate of 23.6 per cent of public expenditure and 4.4 per cent of GDP in 2022 (World Bank, 2025). The 2026/27 budget speech, using the economic classification for central government, lists TZS 7.71 trillion for salaries and staff entitlements in 2025/26, of which TZS 7.02 trillion had been spent by April 2026, against a 2025 GDP of TZS 234.1 trillion (Ministry of Finance, 2026, paras 12, 14, 18).

Two observations follow. First, the registration and plan-completion rates (97.6 and 94.7 per cent) are exactly the kind of completion metrics that this paper argues must be converted into decisions: they show that the system has been populated, not that the appraisal information has changed any management choice. Second, the existence of these systems removes the most common excuse for not using workforce evidence. The question for Tanzanian institutions is no longer whether the data exist, but what they are used for.

Table 3. Tanzania public service workforce indicators from official sources, 2023/24 to 2025/26

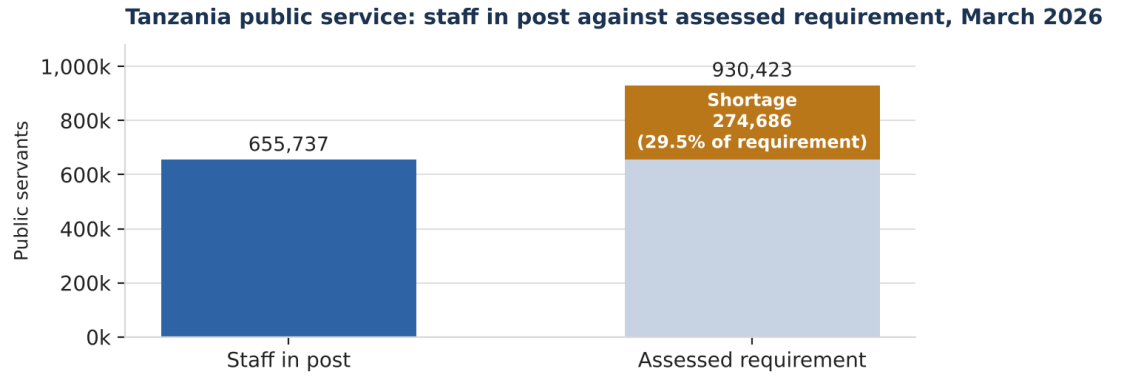
Indicator	Value and period	Source
Institutions enabled to implement PEPMIS/PIPMIS	570 (July 2023 to March 2024)	PO-PSMGG (2024, p. 35)
Public servants registered in PEPMIS/PIPMIS	589,076 of 603,699 (97.6%)	PO-PSMGG (2024, p. 35)
Public servants with performance plans entered	571,586 of 603,699 (94.7%)	PO-PSMGG (2024, p. 35)
Employers on the HR and payroll system; salaries paid	433 employers; TZS 5,519.7 billion (July 2023 to March 2024)	PO-PSMGG (2024, p. 35)
Institutions whose performance plans and contracts were monitored in e-Utendaji	256 (July 2025 to March 2026)	PO-PSMGG (2026, para. 40(xxxv))
Staff in post against assessed requirement (e-Msawazo, 553 of 571 institutions)	655,737 against 930,423; shortage 274,686 (March 2026)	PO-PSMGG (2026, para. 40(xii))
Earlier gap estimate (HR Assessment System)	597,396 staff; shortage 441,366 (May 2024)	Nipashe (2025), reporting the Minister
New recruitment permits 2025/26 (July 2025 to March 2026)	43,866, of which 41,500 new posts and 2,366 for self-financing institutions; 1,345 replacement permits	PO-PSMGG (2026, paras 40(i), 40(vii))
Recruitment permits approved by the President, 2024/25	33,212	Parliament of Tanzania (2025)
New hires per year	7,659 (2020) to 20,158 (2024), an increase of 163%	Nipashe (2025)
Promotions approved through e-Watumishi	20,830 (July 2025 to March 2026)	PO-PSMGG (2026, para. 40(iv))

Indicator	Value and period	Source
Salary arrears verified and paid	TZS 17.74 billion to 13,551 serving staff; TZS 5.53 billion to 1,241 former staff	PO-PSMGG (2026, paras 40(ii), 40(iii))
Public servants' salaries in the national budget, 2025/26	TZS 13.17 trillion of TZS 56.49 trillion (23.3%)	Ministry of Finance (2025, p. 4)

Note. Percentages in the sixth and last rows are calculated by the author from the figures cited. The shortage of 274,686 is described in the source as the requirement for the next five years.

4.2 Chain one: staffing needs assessment to recruitment permits

The clearest Tanzanian example of a metric driving a decision is the national staffing needs assessment. PO-PSMGG reports that the e-Msawazo assessment, covering 553 of 571 public institutions, found 655,737 staff in post against an assessed requirement of 930,423, a shortage of 274,686 over the next five years (PO-PSMGG, 2026, para. 40(xii)). The shortage is about 29.5 per cent of the requirement. Figure 1 shows the gap.



Source: PO-PSMGG budget speech 2026/27, para. 40(xii): e-Msawazo assessment of 553 of 571 institutions. Percentage calculated by the author.

Figure 1. Tanzania public service: staff in post against assessed requirement, March 2026

The decision link is visible in the recruitment permits that followed. The President approved 33,212 recruitment permits in 2024/25 (Parliament of Tanzania, 2025), and PO-PSMGG issued permits for 43,866 new posts between July 2025 and March 2026, of which 41,500 were new positions (PO-PSMGG, 2026, para. 40(i)). The Permanent Secretary reported in October 2025 that 86,500 permits had been issued across the two financial years, with 12,176 of the 2025/26 posts reserved for teachers (as reported by Nipashe, 2025). Annual new hires rose from 7,659 in 2020 to 20,158 in 2024 (Nipashe, 2025).

This chain runs cleanly from activity (the assessment) to metric (the gap) to decision (the permits) to action (recruitment). What it does not yet show is the result link. Were the new teachers deployed to the schools with the highest pupil-teacher ratios? Did waiting times at the dispensaries with the largest shortages fall? The data to answer those questions exist in PO-RALG's education statistics and the Ministry of Health's facility records, but the paper found no published analysis that joins the recruitment decision to a service outcome. The gap itself has also been revised as the assessment methodology matured, from 441,366 in May 2024 (Nipashe, 2025) to 274,686 in March 2026, a reminder that a headline requirement figure depends on how "requirement" is defined.

4.3 Chain two: payroll verification to savings

The second chain is the payroll clean-up of 2016 and 2017, which illustrates a complete loop from metric to measured result. A 2015 audit found that the government had paid TZS 141.4 billion to non-existent workers in a single year, at a time when the February 2016 payroll of TZS 573.7 billion covered 556,418 civil servants (Reuters, 2016a). By May 2016 more than 10,000 ghost workers had been removed, with monthly savings estimated at over TZS 4.5 billion (Reuters, 2016b). By 2017 the verification had identified more than 19,700 ghost workers costing an estimated TZS 238 billion a year, and a separate certificate verification led to the dismissal of more than 9,900 civil servants holding forged qualifications (Reuters, 2017). The Minister of State responsible for the public service reported that the count had reached 19,708 by 31 January 2017 and that the phantom workers had been costing at least TZS 19.8 billion in salaries every month (The Citizen, 2017a). The Controller and Auditor General's report for 2015/16 nevertheless still found TZS 1.4 billion paid to 260 ghost employees across 19 entities, of which only TZS 158 million had been recovered (Daily News, 2017). Payroll integrity remains a live issue a decade later: the CAG's 2024/25 report on local government authorities records 46 institutions holding TZS 12.41 billion in salary arrears outstanding for more than a year, 35 institutions failing to remit TZS 3.90 billion in pension contributions, and salaries of TZS 43.34 million paid to staff who had already left one district council, a recommendation outstanding since 2012/13 (National Audit Office of Tanzania, 2026, pp. xiii, 14).

The payroll case shows what a closed results chain looks like: a reconciliation metric (payroll records against physically verified staff) produced an insight (fictitious or ineligible employees), a decision (removal), an action (payroll deletion and dismissals) and a measurable result (savings in TZS). It also shows a cost that is rarely counted. The World Bank's health workforce assessment notes that no medical personnel were recruited in 2016, the year of the verification freeze (World Bank, 2023). A data-cleaning decision that protected the wage bill also deepened a service shortage. A results chain that stops at savings would have missed this.

4.4 Chain three: appraisal completion to an open question

The third chain is incomplete, and deliberately so. The 94.7 per cent of public servants who entered performance plans into PEPMIS represent an enormous body of structured information on objectives, targets and ratings. The 2026/27 budget speech reports monitoring and analysis of 256 institutions' plans and contracts (PO-PSMGG, 2026, para. 40(xxxv)). What the published record does not yet show is which management decisions that analysis informed: whether rating distributions changed training priorities, whether units with weak contract delivery received different supervision, or whether any institution linked its appraisal data to a service indicator. This is not a criticism of the system, which is young. It is the central question that this paper puts to the APS-HRMNET community and that the practitioner questionnaire in Section 5 begins to answer. The stakes are higher than they appear. The ten-country civil service survey reviewed in Section 2.8 found that performance evaluations whose results do not affect careers or pay have counterproductive effects on performance, and that only performance-oriented promotions were significantly associated with performance (Meyer-Sahling et al., 2018). A 94.7 per cent completion rate is therefore not a neutral achievement: unless the appraisal data visibly inform promotion, development and deployment decisions, the system risks teaching 571,586 public servants that performance planning is a formality. The 20,830 promotions approved through e-Watumishi in 2025/26 (PO-PSMGG, 2026, para. 40(iv)) are the obvious place to test whether e-Utendaji ratings and promotion decisions are connected.

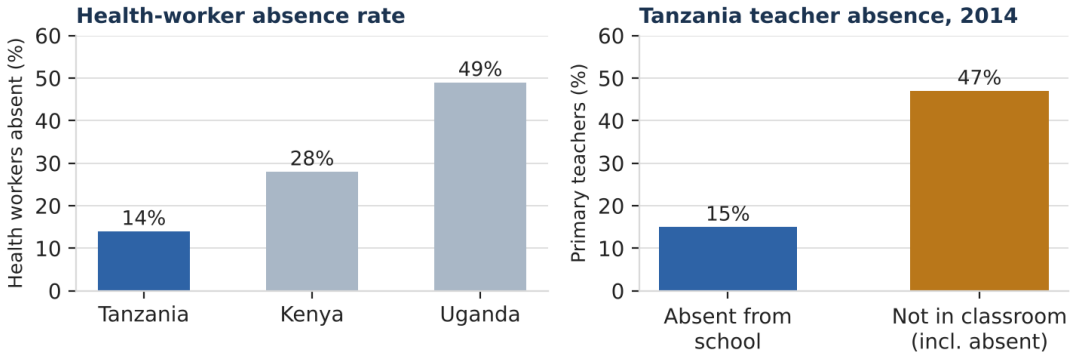
Table 4. Three Tanzanian metric chains read against the results chain

Chain	Metric	Insight and decision	Action and result	Open question
Staffing needs assessment (e-Msawazo)	655,737 staff against 930,423 required; gap 274,686	Shortage concentrated in specific cadres and institutions; recruitment permits issued	41,500 new posts in 2025/26; new hires up 163% since 2020	Were posts deployed to the largest service gaps, and did service indicators move?
Payroll verification (2016 to 2017)	Payroll records against verified staff	More than 19,700 ghost workers and 9,900 forged certificates identified	Removal from payroll; estimated TZS 238 billion a year saved	What did the 2016 recruitment freeze cost in service terms, and has leakage recurred?
Performance management (PEPMIS, now e-Utendaji)	97.6% registered; 94.7% with plans; 256 institutions analysed	Not yet published	Not yet published	Which decisions have the appraisal data changed, and with what effect on services?

Note. Sources as in Table 3 and Section 4.3. The third row records the absence of published evidence, not the absence of use.

4.5 Why headcount alone misleads: deployment and effort

Staffing metrics count bodies. Service outcomes depend on where those bodies are and what they do when they are there. Tanzania's own Service Delivery Indicators (SDI) make the point forcefully. The 2014 round found that rural areas held only 9 per cent of the country's doctors and 28 per cent of its health workforce; that three out of five health workers could not identify severe dehydration in a child; and that, although teacher absence from school had fallen by 40 per cent since 2010, adding 24 teaching days a year, 37 per cent of the teachers who were in school were still not in the classroom, and only one in five teachers mastered the curriculum they taught (World Bank, 2016a). Put differently, 15 per cent of teachers were absent from the school, but 47 per cent, including those absent from school, were not in class during unannounced visits (Filmer et al., 2020, p. 3). Health-worker absence of 14 per cent in Tanzania, down from 21 per cent in 2010 (World Bank, 2016b), compared favourably with 28 per cent in Kenya and 49 per cent in Uganda (World Bank, 2016a); across nine African countries surveyed between 2013 and 2018, 43 per cent of health providers were absent from their facility during an unannounced visit and almost a quarter of teachers were absent from school (Gatti et al., 2021). Figure 2 summarises the comparison. The CAG's audits add the establishment view: in 2016/17 the audited local government authorities were short of 155,013 staff, 32 per cent of their requirement (The Citizen, 2018).

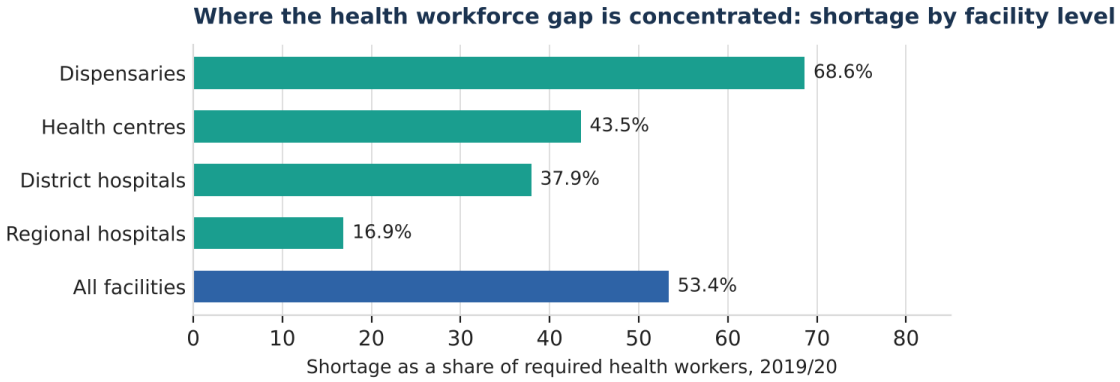


Source: World Bank Service Delivery Indicators (Tanzania 2014; Kenya 2012; Uganda 2013), as reported by World Bank (2016a) and Filmer et al. (2020).

Figure 2. Health-worker absence (Tanzania, Kenya, Uganda) and Tanzanian teacher absence from school and classroom, Service Delivery Indicators

These figures matter for HR analytics because a payroll or establishment report would have counted every one of those teachers as present and employed. The gap between "on the payroll" and "in the classroom teaching" is invisible to headcount metrics and visible only to measures of deployment, attendance and effort. One modelling study estimates that, when teachers who are at school but not in the classroom are counted, about 18.3 per cent of Tanzania's annual education budget, roughly US$394 million, is spent on time not taught (Schipper & Rodriguez-Segura, 2022, p. 16). Whatever the precision of that estimate, the order of magnitude dwarfs the cost of building an attendance indicator.

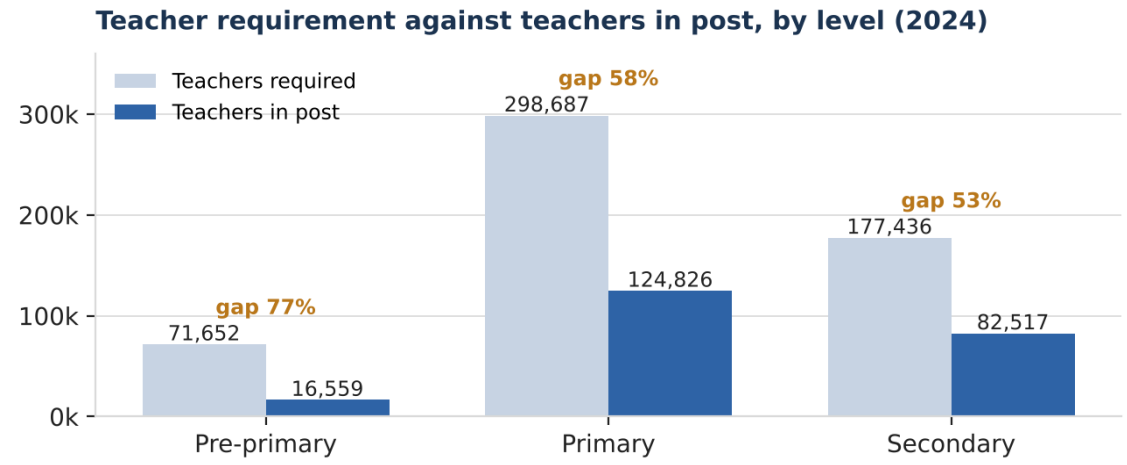
The health sector shows the same pattern in the distribution of shortages. The World Bank's assessment reports that in 2019/20 Tanzania required 212,193 health workers and had 98,987, a shortage of 53.35 per cent, down slightly from 54.12 per cent the year before. The shortage was 68.60 per cent in dispensaries, 43.49 per cent in health centres, 37.93 per cent in district hospitals and 16.86 per cent in regional hospitals. The density of 8.42 clinicians and nurses per 10,000 population in 2019 compared with the WHO benchmark of 22.8. Closing half the gap would require health wage spending to rise by about 0.5 per cent of 2023 GDP, at a time when health's share of the wage bill had fallen from 10 per cent in 2009/10 to under 8 per cent in 2017/18 (World Bank, 2023). The Ministry of Health's own figures tell the same story with different denominators: the National Human Resources for Health Strategy 2020 to 2025 put the shortage at 52 per cent, down from 56 per cent in 2014, with 99,684 health workers available against 209,603 required (Ministry of Health, Community Development, Gender, Elderly and Children, 2020, p. 18), while the 2023 country profile, using a revised requirement of 348,923, reports 119,678 available and a shortage of 66 per cent (Ministry of Health, 2023, p. 17). The three estimates (52, 53 and 66 per cent) differ because the requirement is defined differently, which is the same lesson the national staffing gap teaches: the metric is only as stable as its denominator. Figure 3 shows how steeply the shortage rises as one moves down the facility hierarchy, which is also the direction in which most Tanzanians first meet the health system.



Source: World Bank (2023), Tanzania Human Resources for Health Assessment. Required 212,193; available 98,987.

Figure 3. Health workforce shortage by facility level, 2019/20

Education displays the same structure. PO-RALG statistics reported in 2024 put the requirement at 71,652 pre-primary teachers against 16,559 in post, 298,687 primary teachers against 124,826, and 177,436 secondary teachers against 82,517 (The Citizen, 2024). Figure 4 shows the gaps, which are largest at the pre-primary level where foundational learning begins.



Source: PO-RALG figures as reported by The Citizen (2024). Gap percentages calculated by the author.

Figure 4. Teacher requirement against teachers in post, by level, 2024

The implication for the results chain is direct. The 12,176 teaching posts in the 2025/26 permits are an action. Whether they are a result depends on whether they reached the schools, levels and regions with the largest gaps, and on whether those teachers are in the classroom teaching once they arrive. An HR metric that stops at "posts filled" cannot answer either question. A linked indicator set that pairs posts filled with pupil-teacher ratios by district and with classroom presence can.

> *Tanzania's workforce data infrastructure is no longer the binding constraint. The three chains show that the government already converts metrics into decisions at national scale. What remains thin is published evidence on results: the service changes that followed the decisions. That is the gap this paper's framework is designed to close.*

5. Findings from the Exploratory Practitioner Assessment

5.1 Respondent profile

Table 5. Profile of questionnaire respondents (n = 22)

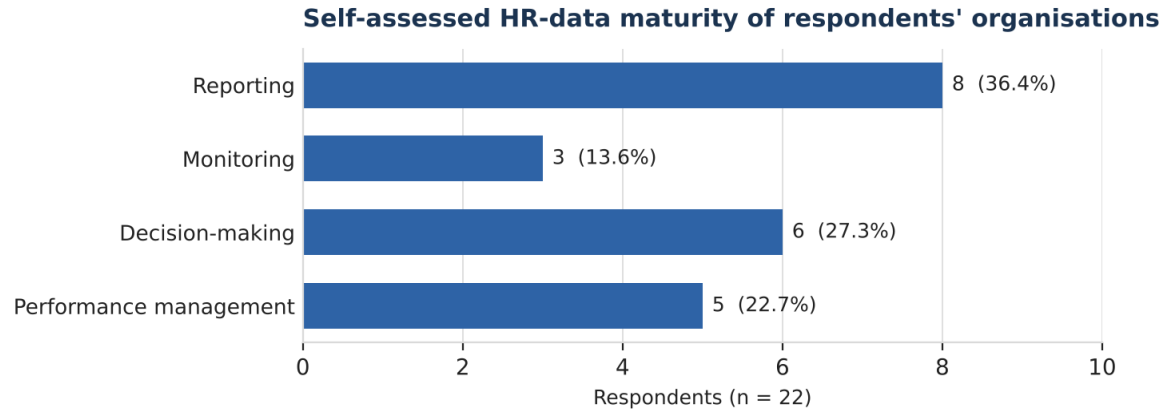
Characteristic	n	%	Notes
Country of work: Tanzania	20	90.9	
Country of work: Kenya	1	4.5	
Country of work: Zimbabwe	1	4.5	
Organisation: ministry	12	54.5	
Organisation: parastatal or state-owned enterprise	5	22.7	
Organisation: local government, executive agency, civil society	4	18.2	Small numbers in each category

Characteristic	n	%	Notes
Organisation: unclassifiable entry	1	4.5	Entry contained a personal name; excluded from the organisation breakdown
Answered the open question on a data-informed decision	16	72.7	Six left the question blank or stated they knew of no example

Note. Percentages are of 22 respondents. The sample is self-selected and dominated by Tanzanian ministries.

5.2 HR-data maturity: reporting remains the most common starting point

Respondents were asked to place their organisation on a four-stage maturity scale: reporting (HR data are compiled and submitted), monitoring (trends are tracked against plans), decision-making (HR evidence informs specific management choices) and performance management (HR evidence is systematically linked to organisational results and used to improve them). Eight respondents (36.4 per cent) selected reporting, three (13.6 per cent) monitoring, six (27.3 per cent) decision-making and five (22.7 per cent) performance management. Half the sample therefore placed their organisation in one of the two more advanced stages, and half in the two earlier stages. Figure 5 shows the distribution.



Source: Exploratory practitioner questionnaire, October 2026 (n = 22). Self-reported; not representative.

Figure 5. Self-assessed HR-data maturity among respondents (n = 22)

Two readings are possible, and the questionnaire cannot distinguish between them. The optimistic reading is that half of the participating institutions already use HR evidence in decisions, which is consistent with the national chains described in Section 4. The cautious reading is that self-assessment inflates maturity: an institution whose managers receive a quarterly HR dashboard may describe itself as "decision-making" even when no decision has changed as a result. The paper's own test of maturity is therefore not the self-rating but the ability to describe a complete chain, which Section 5.6 examines.

The spread also carries a practical lesson. Institutions at the reporting stage need reliable basic records and simple trend tracking; institutions at the decision-making stage need follow-up routines that check whether decisions produced results. A single national template or platform will not serve both. What does serve both is the discipline of asking, for every metric reported, what decision it is meant to inform.

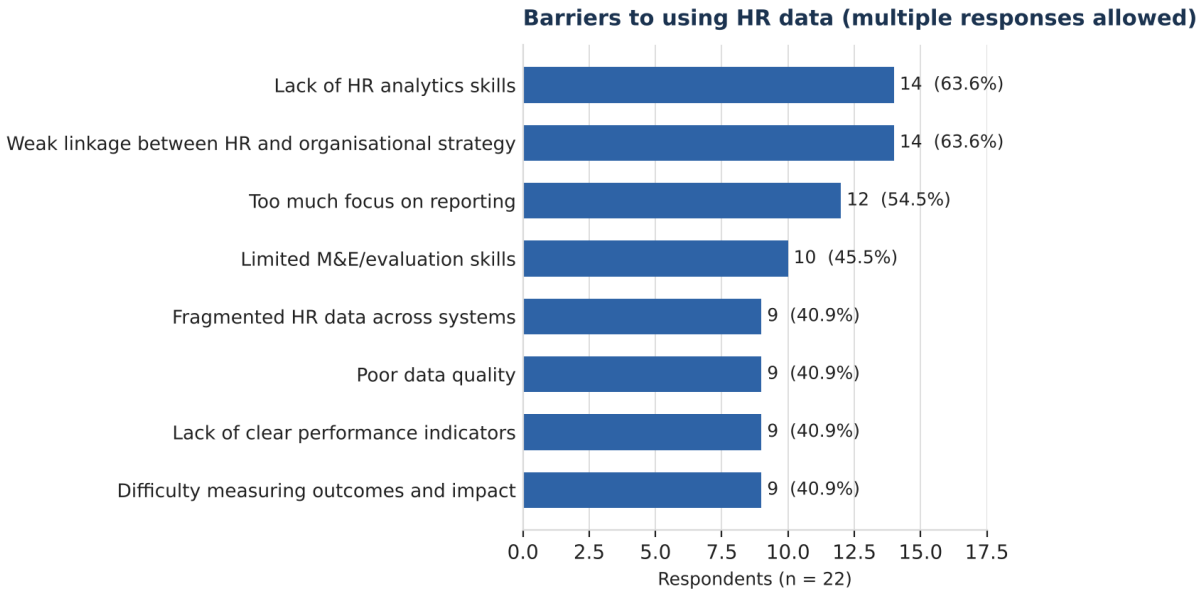
5.3 The gap is about skills and strategy at least as much as technology

Respondents could select any number of barriers. The two most frequently selected were a lack of HR analytics skills (14 of 22, 63.6 per cent) and weak linkage between HR and organisational strategy (14, 63.6 per cent), followed by too much focus on reporting (12, 54.5 per cent) and limited M&E or evaluation skills (10, 45.5 per cent). Fragmented HR data across systems, poor data quality, a lack of clear performance indicators and difficulty measuring outcomes and impact were each selected by nine respondents (40.9 per cent). Table 6 and Figure 6 present the full distribution.

Table 6. Barriers to the use of HR data selected by respondents (multiple responses allowed)

Barrier	n	% of 22	Type of barrier
Lack of HR analytics skills	14	63.6	Capability
Weak linkage between HR and organisational strategy	14	63.6	Institutional
Too much focus on reporting	12	54.5	Institutional
Limited M&E or evaluation skills	10	45.5	Capability
Fragmented HR data across systems	9	40.9	Technical
Poor data quality	9	40.9	Technical
Lack of clear performance indicators	9	40.9	Institutional
Difficulty measuring outcomes and impact	9	40.9	Methodological

Note. The barrier types in the final column are the author's classification, added to show that capability and institutional barriers were selected more often than technical ones.



Source: Exploratory practitioner questionnaire, October 2026 (n = 22). Self-reported; not representative.

Figure 6. Barriers to using HR data selected by respondents (multiple responses allowed)

The pattern deserves emphasis because it runs against a common assumption. The barriers selected most often are not technical. Fragmented systems and poor data quality, the two barriers that a software procurement would address, were selected by 41 per cent of respondents; the skills and strategy barriers

were selected by 64 per cent. This mirrors findings from very different settings. Gartner's surveys of HR leaders found that the share of organisations piloting or implementing generative AI rose from 19 per cent in June 2023 to 61 per cent in January 2025, while only 8 per cent of HR leaders believed their managers had the skills to use AI effectively and only 14 per cent of organisations were supporting managers to integrate it (Gartner, 2025a, 2025b). Adoption outruns capability in large private-sector organisations as much as in African ministries. The practical question for an institution is therefore not which tool to buy but which questions its managers are equipped to ask.

The open-ended responses echoed the pattern. Several respondents described a weak connection between HR indicators and institutional performance, while others referred to analytical skills, data interpretation, connectivity between systems, information sharing and the absence of measurable indicators. The comments align with the paper's central claim: collecting more numbers does not close the gap. Clarity about the management question, stronger analytical practice and a willingness to act on the evidence do.

5.4 Practitioners see potential in AI and recognise its risks

Respondents most often selected skills-gap analysis (17 of 22, 77.3 per cent) and workforce forecasting (16, 72.7 per cent) as areas where AI could add value, followed by productivity analysis (14, 63.6 per cent), employee performance analysis (12, 54.5 per cent), employee engagement analysis (11, 50.0 per cent) and recruitment analytics (10, 45.5 per cent). The two most selected uses are aggregate and planning-oriented rather than individual and evaluative, which is consistent with the lower-risk starting points recommended in Section 7.

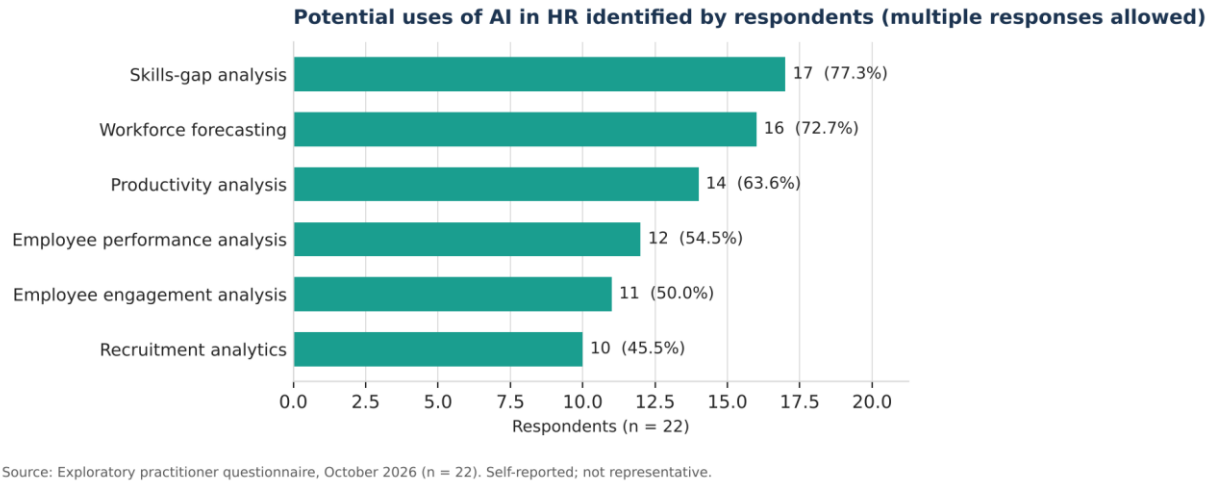


Figure 7. Potential uses of AI in HR identified by respondents (multiple responses allowed)

At the same time, data privacy was the most frequently selected risk (16 of 22, 72.7 per cent), followed by cybersecurity (12, 54.5 per cent), poor-quality data producing misleading results (10, 45.5 per cent), lack of human oversight (10, 45.5 per cent), ethical concerns (9, 40.9 per cent) and lack of transparency or explainability (7, 31.8 per cent). Table 7 sets opportunities and risks side by side.

Table 7. Potential AI uses and AI risks selected by respondents (multiple responses allowed)

Potential use	n	%	Risk	n	%
Skills-gap analysis	17	77.3	Data privacy	16	72.7

Potential use	n	%	Risk	n	%
Workforce forecasting	16	72.7	Cybersecurity	12	54.5
Productivity analysis	14	63.6	Poor-quality data producing misleading results	10	45.5
Employee performance analysis	12	54.5	Lack of human oversight	10	45.5
Employee engagement analysis	11	50.0	Ethical concerns	9	40.9
Recruitment analytics	10	45.5	Lack of transparency or explainability	7	31.8

Note. n = 22. Respondents could select more than one option in each list.

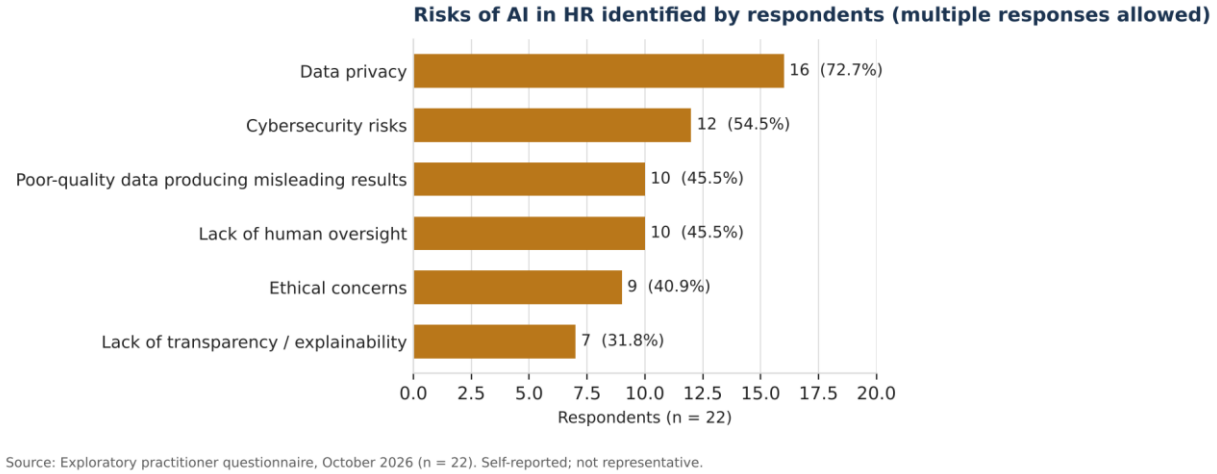
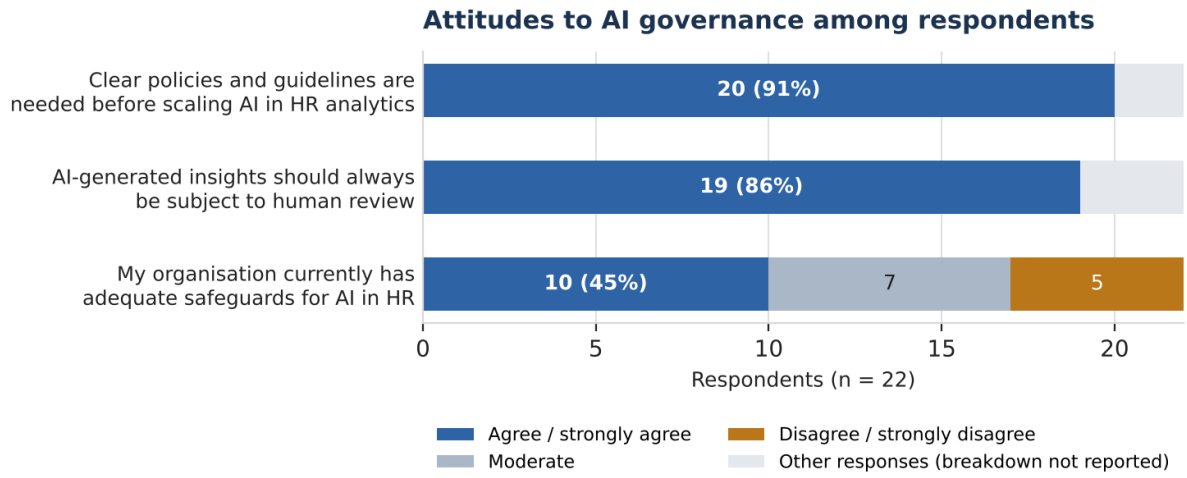


Figure 8. Risks of AI in HR identified by respondents (multiple responses allowed)

The combination matters. Practitioners are not simply asking for automation; they are signalling that safeguards, data quality and accountability must come with it. The prominence of privacy is notable in a country where the Personal Data Protection Act, 2022 is recent and its regulatory practice still forming. It is also consistent with the international evidence that employment-related AI is among the highest-risk applications: the European Union's AI Act lists AI used for recruitment, selection, promotion, termination, task allocation and the monitoring and evaluation of workers' performance as high-risk systems subject to conformity assessment and human oversight (Regulation (EU) 2024/1689, Annex III, point 4).

5.5 Attitudes to AI governance

Three attitude statements sharpen the picture. Twenty of 22 respondents (90.9 per cent) agreed or strongly agreed that clear policies and guidelines are needed before scaling AI in HR analytics. Nineteen (86.4 per cent) agreed or strongly agreed that AI-generated insights should always be subject to human review. By contrast, only ten (45.5 per cent) agreed or strongly agreed that their organisation currently had adequate safeguards; seven were moderate and five disagreed or strongly disagreed. Figure 9 presents the three items.



Source: Exploratory practitioner questionnaire, October 2026 (n = 22). Self-reported; not representative.

Figure 9. Attitudes to AI governance among respondents (n = 22)

These are self-reports, not an audit of safeguards. But the gap between what practitioners say should exist (policies, human review) and what they say does exist (adequate safeguards) is large: 91 per cent against 45 per cent. It points to a governance deficit that is perceived from inside institutions, not only diagnosed from outside. The paper treats this as the strongest finding of the questionnaire, because it indicates demand for the governance measures recommended in Section 7 rather than resistance to them.

5.6 Examples of data-informed decisions: promising, but the chain stops early

Sixteen respondents offered an example of HR data influencing a management decision. The examples included recruitment delays prompting the use of talent pools, staff shortages informing recruitment requests, training-needs information shaping training plans, turnover data feeding succession planning, staff deployment decisions, the identification of performance gaps and the use of the public employee performance management system. Several answers were brief, and some stated that the respondent knew of no example.

Read against the results chain, the examples cluster at the decision and action links. A shortage leads to recruitment; a training need leads to training. Almost none continued to the result link: whether the vacancy was filled in time, whether the recruit was deployed where the gap was, whether the service indicator moved. This is the same pattern that Section 4 found in the national chains. The absence of a documented result does not mean the intervention failed; it means the contribution has not yet been demonstrated. The difference between an institution at the decision-making stage and one at the performance-management stage is precisely whether it routinely closes that loop.

5.7 Reading the findings against external evidence

Three external reference points help to calibrate the findings. First, the APS-HRMNET community itself resolved at its 8th conference in Nairobi in November 2023 to develop skills in metrics and data analytics and to strengthen HR planning (Samilu, 2023); the skills barrier that 64 per cent of respondents selected is one the network has already recognised. Second, the ILO's analysis of generative AI exposure finds that in

low-income countries only 0.4 per cent of employment is potentially exposed to automation, while 10.4 per cent is exposed to augmentation, and that clerical work, which includes much HR administration, is the most exposed occupational group, with 24 per cent of its tasks highly exposed and a further 58 per cent at medium exposure (Gmyrek et al., 2023). For African public HR functions, the realistic near-term effect of AI is augmentation of analysis, not replacement of staff, which matches the planning-oriented uses that respondents prioritised. Third, the engagement data that HR functions increasingly collect connect to performance only weakly unless they are acted upon: Gallup reports that 20 per cent of employees worldwide and 19 per cent in Sub-Saharan Africa were engaged at work in 2025, with 46 per cent of Sub-Saharan African employees reporting daily stress (Gallup, 2026). An engagement score is a metric; whether it changes supervision, workload or career pathways is the decision.

5.8 Interpreting the assessment with appropriate caution

The results are signals, not estimates. The assessment included 22 self-selected respondents, mostly from Tanzanian ministries. It cannot establish the prevalence of any barrier across African public institutions, nor can it show that a barrier causes lower performance. The fact that 14 respondents selected limited HR analytics skills means that the option was common in this group; it does not mean that 64 per cent of African public institutions lack such skills.

Perceptions and institutional facts are different evidence types. Respondents' views on whether safeguards exist signal confidence or concern; they do not replace a data-protection assessment, a cybersecurity review or an examination of actual decision records. The appropriate next step is to use these perceptions to frame testable questions and then verify them through document review, interviews and system checks. Small exploratory assessments remain useful for exactly this purpose: they identify issues that deserve attention and help design a larger study. Their value depends on transparent methods, cautious language and a clear line between what the data show and what the author infers. In this paper the findings motivate the framework and recommendations; they do not claim that HR analytics has already improved service outcomes.

6. Discussion: Making the "So What?" Question Routine

The literature, the official statistics and the questionnaire point to four connected shifts. HR reporting needs to begin with an institutional question rather than a list of available indicators. HR data should be interpreted alongside operational and service-delivery evidence. Management must decide, act and then check what changed. And digital tools and AI should strengthen professional judgement, accountability and employee rights rather than bypass them. The results chain is the practical device for making these shifts routine.

6.1 A practical HR results chain

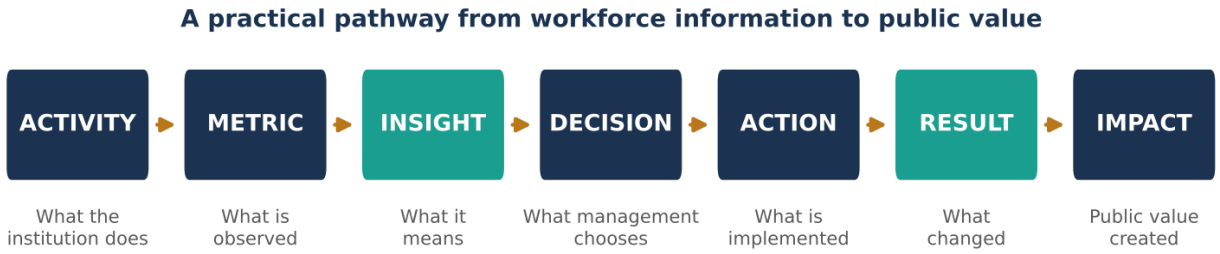


Figure 10. The HR evidence-to-impact results chain

Each link has a defined meaning and a test. **Activity** is what the institution did: for example, training frontline staff on a revised inspection procedure. **Metric** is what was measured: the proportion of relevant staff completing the training. **Insight** is what the evidence suggests and what other explanations are plausible: completion is high, but observation shows that staff apply the procedure inconsistently. **Decision** is the management choice: targeted coaching and clearer supervision responsibilities. **Action** is what was implemented, by whom and by when: supervisors conduct monthly observations and feedback sessions. **Result** is the observed change: the proportion of inspections completed correctly and on time rose. **Impact** is the wider public value: more reliable inspections, fewer repeat visits and greater confidence in the service.

The chain is most useful when each link is explicit and owned. An indicator should have a definition, data source, frequency, responsible officer, disaggregation, baseline and target. The insight should record the interpretation and its uncertainties. The decision should name an accountable manager. The action should have a deadline. The result should be reviewed after a suitable interval against a comparison, whether over time or across comparable units, with alternative explanations considered. This is contribution analysis in everyday management form: the institution builds a plausible account of how its action contributed to the observed change, tests that account against the evidence and the alternatives, and states the confidence the evidence warrants (Mayne, 2012). The chain is a thinking tool, not a claim that every public-service outcome can be attributed to one HR intervention.

Table 8. Illustrative HR metrics and the management question each should answer

HR metric	The "so what?" question	Evidence of a meaningful result
Training completion	Did staff gain and apply relevant skills?	Observed competence; quality or error measures
Time to recruit	Were critical service bottlenecks reduced?	Vacancy duration in critical posts and service waiting time
Appraisal completion	Did feedback lead to improved work?	Completed development actions and service outcomes
Turnover	Which critical capabilities were lost, and why?	Retention in key roles and service continuity
Staff in post against requirement	Are the gaps where the service gaps are?	Deployment against workload; pupil-teacher ratio or patient load by location
Attendance	Are staff who are paid also present and working?	Classroom or clinic presence; teaching days or consultations delivered

Note. Conceptual examples, not survey findings.

6.2 Illustrative use cases for public institutions

Vacancies and service delays. A vacancy rate becomes useful when disaggregated by critical role, location, duration and service function. If applications are delayed in a district office, the analysis should test whether staffing is the main bottleneck or whether approvals, equipment, workflow or demand are more influential. Recruitment action can then be assessed against a service indicator such as processing time or backlog. The e-Msawazo gap figures already provide the first disaggregation; the service indicators are held by sector ministries and PO-RALG.

Training and capability. Training attendance is an output, not proof of learning or performance improvement. A stronger approach combines a skills-gap assessment, learning completion, an assessment of acquired competence, evidence of application at work and a relevant service or quality indicator. The training-evaluation literature reviewed in Section 2.3 shows that training reliably changes knowledge, that behaviour change depends on the work environment, and that results at the organisational level are the hardest to demonstrate. If service performance does not improve, managers should ask whether the training was relevant, whether staff had the opportunity to apply it and whether systems supported the new behaviour.

Turnover and retention. Aggregate turnover can hide concentrated losses in scarce or critical roles. Analysis should examine role, tenure, location, reasons for leaving and recruitment lead times, with privacy safeguards. Where a pattern is identified, management can test responses such as better onboarding, career development, workload review or succession planning and monitor whether retention and continuity improve.

Performance appraisal. Completion rates show that a process was completed, not that goals were meaningful, feedback useful or performance improved. With 94.7 per cent of Tanzanian public servants now holding performance plans in the system, the next analytical step is to examine the quality of objectives, the distribution of ratings, the completion of development actions and the alignment between individual or team objectives and institutional priorities.

6.3 Worked example: from a training dashboard to service improvement

Step 1: identify the service problem. Suppose a regulatory institution finds that inspection reports are frequently returned for correction. The initial question is not how many staff attended training; it is whether gaps in staff capability contribute to report errors and what other factors may be involved.

Step 2: combine relevant evidence. HR data show which inspectors completed training, their roles and experience and whether they received coaching. Operational data show error types, inspection complexity, workload, equipment availability, supervisory review and turnaround time. Interviews with inspectors and supervisors explain patterns that administrative data cannot.

Step 3: choose a proportionate response. If the evidence points to a specific skills gap, the institution might introduce targeted practice, job aids and supervisor feedback. If the main cause is unclear guidance or inadequate equipment, additional training will not solve the problem. The response should match the diagnosed cause, which is the practical meaning of the ability-motivation-opportunity perspective discussed in Section 2.2.

Step 4: measure change and examine alternative explanations. The institution compares the proportion of reports accepted without correction before and after the intervention, alongside turnaround time and workload. It records whether procedures or staffing changed during the same period. A before-and-after comparison provides useful monitoring but does not by itself prove causation; where the decision is consequential or costly, a stronger evaluation design is warranted.

Step 5: decide what to do next. If errors decline and the evidence supports the intervention, managers continue or extend it. If there is no change, they revisit the diagnosis. If some groups benefit and others do not, the institution investigates differences in supervision, access to training or work conditions. The measure begins a management inquiry rather than ending it.

6.4 Worked example: workforce forecasting and deployment

The question. A local government authority or service agency may face uneven workloads across locations. An overall headcount can look adequate even while some facilities have critical shortages and others have capacity that could be redeployed. The World Bank's health figures make the point: a national shortage of 53 per cent conceals a 69 per cent shortage in dispensaries and a 17 per cent shortage in regional hospitals (World Bank, 2023). Workforce forecasting can help estimate future needs, but it should be based on service demand and task requirements, not simply on last year's staffing pattern.

The evidence. Useful information includes authorised and filled posts, staff skills, retirement eligibility where lawfully available, recruitment lead times, workload, population served, seasonal demand, service standards and geographic access. Data should be checked for gaps and inconsistent classifications. Forecasts should include assumptions and uncertainty ranges rather than a single number presented as certainty. This is where AI-assisted forecasting can add value, provided the inputs are trustworthy and the outputs are reviewed.

The management response. Options include recruitment, internal mobility, cross-training, workflow redesign or temporary support. The OECD discusses strategic mobility as a way to allocate public-service skills to emerging priorities (OECD, 2023). Mobility should be designed fairly, with transparent criteria and attention to employees' circumstances.

The result to monitor. The institution tracks whether critical posts are covered, whether workload becomes more balanced, whether service delays decline and whether turnover or absence changes. It also checks for unintended consequences, such as transferring a shortage from one location to another. The forecast is useful only if it informs a decision and is updated as conditions change.

6.5 Worked example: retention, engagement and employee trust

Avoid reducing people to a risk score. A high turnover rate can signal a serious organisational issue, but it does not tell managers what is wrong. Exit interviews, staff surveys, workload data, promotion opportunities, location, pay structures and supervisory practices may all be relevant. Engagement scores help identify themes, but they are not a complete measure of morale or a substitute for listening to staff.

Use data to open a conversation. If a unit shows lower engagement and higher turnover than comparable units, leaders can investigate confidentially and involve employees in developing solutions. The purpose is to improve working conditions and continuity, not to label individuals as disloyal or likely to leave. Small teams require particular care because anonymised results can still identify people.

Evaluate the response. If management changes onboarding, mentoring, workload allocation or career-development access, it should specify the expected mechanism and review results after a reasonable period. Retention may improve for reasons unrelated to the intervention, and staff may remain because they lack alternatives rather than because conditions improved. Combining administrative trends with qualitative feedback gives a more credible account.

6.6 What AI can and cannot add at each link

AI tools are best understood by the link of the chain at which they operate. Table 9 maps common applications to the links, the value they can add and the safeguard each requires. Two patterns stand out. AI adds most at the metric and insight links, where it can clean, join and pattern-match large datasets faster than manual reporting. It adds least, and risks most, at the decision link, where accountability, fairness and legal responsibility cannot be delegated to a model. The Amazon recruiting tool that penalised résumés containing the word "women's" (Dastin, 2018) and the ongoing collective action alleging age discrimination by an AI screening system (Mobley v. Workday, Inc., 2025) are reminders that a model trained on historical decisions reproduces their biases with new confidence.

Table 9. What AI can add at each link of the results chain, and the safeguard each use requires

Link	Typical AI application	Value added	Required safeguard
Metric	Automated data cleaning, record matching, anomaly detection in payroll and attendance	Faster, more complete and more consistent indicators; early detection of ghost workers or duplicate records	Data-quality rules; audit trail; lawful basis under the Personal Data Protection Act, 2022
Insight	Pattern analysis across HR, finance and service data; skills-gap analysis; workforce forecasting	Reveals concentrations of shortage, absence or turnover that aggregates hide; scenario forecasts with uncertainty ranges	Documented assumptions; testing on held-out data; bias checks across groups; explanation appropriate to the use
Decision	Recommendation or ranking of individuals (recruitment, promotion, discipline)	Limited: a prediction is not an explanation and cannot carry accountability	Human decision rights; right to contest; treated as high-risk (EU AI Act Annex III, point 4); avoid until governance is mature
Action	Workflow automation (permits, transfers, leave) through portals	Reduced administrative delay; freed capacity for analysis	Access control; logging; fallback for system failure
Result and impact	Automated monitoring of linked service indicators; dashboards that pair HR and service data	Keeps the result link visible; prompts follow-up reviews	Indicators chosen for the decision, not for data availability; periodic review of indicator consequences

Note. Author's synthesis of Sections 2.8 and 2.9.

Table 10. Illustrative links between HR signals, management action and the outcome to review

HR signal	Question to investigate	Possible management action	Outcome to review
High vacancy rate in critical roles	Are vacancies causing delays, or are other process constraints more important?	Recruit, redeploy, redesign workflow or address approval delays based on diagnosis	Critical-post coverage, turnaround time, backlog
High training completion, unchanged quality	Was competence gained and applied? Are tools and supervision adequate?	Targeted coaching, job aids, supervisory support or redesigned training	Error rate, rework, service quality

HR signal	Question to investigate	Possible management action	Outcome to review
High turnover in a specialist unit	Which roles and tenure groups are leaving, and why?	Improve onboarding, career paths, workload or management practice where evidence supports it	Retention in critical roles, continuity, vacancy duration
Uneven workload across locations	Does staffing match demand, skill mix and geographic access?	Transparent deployment, mobility, cross-training or recruitment	Workload balance, access, waiting time
High appraisal completion, little development	Are objectives useful and are development actions followed through?	Improve objective-setting, feedback and follow-up accountability	Quality of objectives, completed development actions, team results
Staff paid but absent	Is absence concentrated by facility, cadre or day of week, and why?	Attendance monitoring, supervision, transport or workload remedies matched to cause	Teaching days or consultations delivered; service user experience

7. Recommendations for Public Institutions

The recommendations below are addressed to heads of institutions, HR directors, planners and M&E units in African public services. They are ordered from the least to the most demanding, and none of the first six requires new technology.

1. **Start with a decision, not a dashboard.** For each priority HR indicator, state the management question it answers and the decision that could follow. Retire indicators that are collected but never used, unless they serve a statutory or accountability requirement. Behn's (2003) reminder that different purposes require different measures applies: an indicator that is good for accountability reporting may be useless for learning.
2. **Build a small set of linked measures.** Pair HR measures with service or programme measures: staffing in critical roles with waiting times, inspection coverage, case backlogs, error rates or service-user experience. Tanzania's e-Msawazo gaps, PO-RALG's pupil-teacher ratios and the Ministry of Health's facility data already exist; the work is to put them in the same table.
3. **Strengthen data quality and interoperability.** Agree common definitions, unique identifiers where lawful, update responsibilities and validation checks. Document missing data and inconsistent categories. Connect HR information with planning, finance and service-delivery information only where there is a legitimate purpose and adequate governance under the Personal Data Protection Act, 2022.
4. **Invest in practical analytical capability.** Develop the skills of HR, M&E, planning and service managers in data interpretation, visualisation, problem analysis, evaluation questions and communicating uncertainty. The 8th APS-HRMNET conference resolved to do exactly this (Samilu, 2023); the 64 per cent of respondents who selected the skills barrier suggest that the resolution has not yet reached most institutions. Joint analysis across functions prevents HR from becoming an isolated reporting unit.
5. **Create a regular evidence-to-action meeting.** At an agreed interval, managers review a small number of workforce indicators alongside institutional performance and record the question, evidence, decision, responsible person, deadline and follow-up result. The research on performance

information use is consistent that leadership attention, goal clarity and a culture that treats data as a tool for learning rather than blame are the strongest predictors of use (Kroll, 2015; Moynihan & Pandey, 2010). The meeting is where those conditions are created.

6. **Evaluate important interventions proportionately.** Use a simple theory of change and establish baseline information before major HR interventions. For important initiatives, use time-series comparisons, comparison groups or other appropriate methods where feasible. Report contribution carefully and distinguish association from causation.
7. **Govern AI before scaling it.** Start with lower-risk, aggregate use cases such as workforce forecasting and skills-gap analysis, which respondents themselves prioritised. Before deployment, assess purpose, data quality, privacy, cybersecurity, bias, explainability, procurement and accountability using a recognised structure such as the NIST AI Risk Management Framework's Govern, Map, Measure and Manage functions (National Institute of Standards and Technology, 2023). Require human review for consequential decisions and provide routes to correct data or challenge decisions.
8. **Protect trust and dignity.** Explain what employee data are collected, why, who can access them and how they will be used. Limit collection to what is necessary, set retention rules, consult staff representatives and prohibit covert or disproportionate surveillance. The UNESCO Recommendation's emphasis on human dignity, privacy and human oversight (UNESCO, 2022) applies to employees as much as to citizens.
9. **Make learning part of performance management.** Treat unexpected or disappointing results as prompts for inquiry rather than automatic evidence of individual failure. Psychological safety is a precondition for honest data (Edmondson, 1999): a system that punishes every adverse finding produces concealment and superficial compliance.
10. **Share practice across institutions and link workforce evidence to national performance reporting.** Public-service networks can exchange indicator definitions, anonymised case examples, evaluation methods and lessons from responsible digital HR systems. Within Tanzania, the Government Performance Report process offers a natural home for a workforce chapter that pairs e-Msawazo gaps and e-Utendaji data with service indicators for priority sectors.

7.1 A practical indicator catalogue

Table 11. A practical indicator catalogue for public institutions

Domain	Candidate indicators	Interpret alongside
Workforce availability	Vacancy rate in critical roles; median time to fill; proportion of posts filled by staff with required skills; deployment against workload; time to onboard	Service demand; process bottlenecks; e-Msawazo requirement by cadre
Presence and effort	Attendance by facility or school; proportion of paid staff present at unannounced check; teaching days or consultations delivered	Transport, supervision and workload data; SDI benchmarks
Capability and learning	Assessed skills gaps; competence demonstrated after learning; application of skills at work; proportion of agreed development actions completed	Training attendance reported as an output, never as proof of capability

Domain	Candidate indicators	Interpret alongside
Workforce stability and wellbeing	Voluntary turnover in critical roles; absence patterns; retention by tenure; workload distribution; employee feedback	Confidential handling; no unsupported inferences about individual motivation or health
Performance and service quality	Service turnaround time; error or rework rates; backlog; compliance; coverage; complaints; service-user experience	Institutional mandate; the indicator is chosen for the decision, not because the data are easy to obtain
Fairness and inclusion	Differences in recruitment, development, deployment or appraisal outcomes across relevant groups, where lawful and safe	Privacy safeguards and contextual analysis; a difference is a signal for investigation, not proof of discrimination
Payroll integrity	Payroll records reconciled against verified staff; duplicate identifiers; arrears outstanding	Audit findings; cost of verification freezes in service terms

7.2 Data governance and responsible AI: a checklist

Data governance is the foundation of trustworthy analysis. Each key dataset should have a responsible owner, an operational steward, documented definitions and an update schedule, with responsibilities covering accuracy, correction, access, retention and incident escalation. Governance should not be left entirely to IT teams: HR and service managers understand the meaning of the records, while information-security and legal specialists establish the controls. Employee records contain sensitive details and should not be copied into general-purpose AI tools without authorisation and an assessment of privacy and security implications. Table 12 translates the NIST functions into HR practice and anchors each in the Tanzanian legal and policy context.

Table 12. Responsible AI in HR: the NIST functions applied to public-service HR analytics

Function	What it means for HR analytics	Tanzanian anchor	International reference
Govern	Assign accountable owners for HR data and any AI tool; publish a short policy on purpose, permitted uses, human review and redress; train managers	Personal Data Protection Act, 2022 (in force 1 May 2023) and its 2023 Regulations; Public Service Act, 2002 (Cap. 298); e-Government Act, 2019	NIST (2023); OECD (2024); UNESCO (2022)
Map	State the decision each tool supports, who is affected, what harm a wrong output could cause, and whether the use is high-risk (individual ranking) or lower-risk (aggregate forecasting)	Institutional data-protection impact assessment	EU AI Act Annex III, point 4 as a risk benchmark
Measure	Test accuracy, bias across groups, privacy exposure and explainability before use and periodically after; document model version and known limits	Data quality audits under PO-PSMGG and CAG oversight	NIST (2023); International Organization for Standardization (2023)
Manage	Monitor outputs in use; keep humans in the decision for consequential cases; give employees a route to correct records and contest decisions; retire tools that fail tests	Public Service Commission grievance mechanisms	Berg and Johnston (2025); Cappelli and Rogovsky (2023)

Note. The NIST framework is voluntary and does not substitute for Tanzanian law or government policy; it offers a practical structure for due diligence.

8. An Implementation Roadmap

A practical start does not require an analytics platform. Institutions can begin with existing information and one focused management problem. A phased approach is recommended, and it is deliberately modest: the aim of the first cycle is to complete one results chain end to end, not to transform the institution.

Table 13. A 90-day cycle and a 12-month horizon for turning HR metrics into performance

Phase	Actions	Output
Days 1 to 30	Choose one service-delivery problem where workforce factors plausibly matter; identify the decision-maker; map the HR and operational data already available; name an owner for each indicator	A one-page problem statement and data map
Days 31 to 60	Agree indicator definitions and a simple results chain; check data quality; establish a baseline; list plausible alternative explanations for any change	Indicator definitions, baseline and theory of change
Days 61 to 90	Review the evidence with HR, M&E, planning, finance and service managers; agree one or two actions; assign responsibilities and deadlines; record the decision	A recorded decision with owner and deadline
Months 4 to 9	Implement; monitor the linked service indicator monthly; hold the evidence-to-action meeting at an agreed interval	Monitoring record and interim review
Months 10 to 12	Revisit the measures; document what changed and what did not; decide whether to adapt, scale, stop or evaluate more rigorously; share the case within the institution and the network	A documented results-chain case and a decision on the next cycle

AI should not be the first step if the underlying question, data and governance are not ready. In many institutions a validated spreadsheet, a shared data dictionary and a monthly management discussion will produce more value than a predictive system that no one fully understands. Once the first cycle has shown where analysis is slow or where patterns are hard to see, the case for AI-assisted tools can be made on evidence rather than on expectation.

8.1 Monitoring whether the framework itself is working

Table 14. Indicators for monitoring the framework's own implementation and results

Level	What to monitor	What it shows
Implementation	Priority indicators have clear definitions; data are updated on time; management reviews record decisions and owners; agreed actions are completed	Whether the routine is operating; not yet evidence of improved service
Intermediate outcomes	Improved skills; faster recruitment; better deployment; fewer errors; improved retention in critical roles; completion of development actions	Whether workforce conditions are changing in the expected direction; needs baselines and realistic timeframes
Service outcomes and unintended effects	The relevant service measure; costs; fairness; unintended consequences such as faster processes with lower quality or lower turnover that reflects blocked mobility	Whether public value has improved and at what cost

Level	What to monitor	What it shows
Review and adaptation	Periodic review with HR, M&E, finance, planning, operational managers and staff representatives; retirement of measures that no longer support decisions	Whether the system is living rather than a compliance template

9. Limitations and Future Research

The practitioner assessment has clear limitations. It includes 22 self-selected responses, dominated by Tanzanian ministries, and measures perceptions rather than audited practice. Only 16 respondents answered the question on data-informed decisions, and one organisation-type response was unusable. The official statistics are stronger but have their own limits: the staffing gap has been revised as the assessment methodology matured, the two published wage-bill figures for 2025/26 differ in coverage, several press-reported figures could not be traced to the primary government release, and the most recent nationally representative absence data are from 2014. The paper states each of these limits where the figure is used.

Future work could proceed on three fronts. First, a larger and more diverse survey, with interviews of HR and service-delivery leaders, could test whether institutions at higher self-assessed maturity are in fact more likely to document complete results chains, controlling for size, resources, digital maturity and mandate. Second, longitudinal case studies could follow a specific HR intervention, such as the deployment of the 12,176 teaching posts approved for 2025/26, from decision to deployment to pupil-teacher ratio and learning outcome, reporting mixed and negative results as well as successes. Third, responsible-AI evaluations in African public services could test tools against explicit criteria: predictive accuracy, fairness across groups, privacy, explainability, cost, user trust and actual decision usefulness, including whether human reviewers meaningfully override incorrect outputs. Research should include frontline workers, HR practitioners, managers, staff associations and service users, and should examine whether tools work across urban and rural settings, languages, variable connectivity and diverse administrative capacities.

10. Conclusion

Public institutions do not become more effective because they collect more workforce data. They become more capable when they use reliable information to ask better questions, understand the causes of performance problems, make considered decisions and learn from the results. Tanzania's experience shows both halves of this proposition. The country now registers 97.6 per cent of its public servants in a performance management system, measures its staffing gap institution by institution, and has converted that measurement into tens of thousands of recruitment permits. It has also shown, in the payroll clean-up, what a closed loop from metric to measured saving looks like. What the published record does not yet show is the result link for the largest decisions: whether the new posts reached the dispensaries with 69 per cent shortages and the pre-primary classrooms with 77 per cent gaps, and whether the staff who arrived are present and teaching.

The practitioners who answered the questionnaire describe the same unfinished chain from inside their institutions. Half place their organisation at the reporting or monitoring stage. Nearly two-thirds name analytical skills and weak links to strategy, not technology, as the main barriers. Nine in ten want policies and human review before AI is scaled, while fewer than half believe their safeguards are adequate. These

are not the responses of a profession resisting evidence; they are the responses of one asking for the conditions in which evidence can be used.

The answer is neither to abandon HR metrics nor to automate every decision. It is to give each important metric a clear purpose and a place in a results chain, to pair it with the service indicator it is meant to move, to decide and act, and to check whether the action made a difference. HR professionals, M&E specialists, planners and service managers can make workforce evidence part of ordinary management rather than a report that is read once and filed. When AI is used, it should strengthen transparent, fair and accountable decisions, with people retaining responsibility for consequential choices. Measure what matters. Understand what it means. Act on the evidence. Then check whether it worked.

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Appendix A. Summary of the Exploratory Practitioner Assessment

Respondent profile. 22 responses; 20 identified Tanzania, one Kenya and one Zimbabwe as the country of work. Organisation categories were mainly ministries (12) and government parastatals or state-owned enterprises (5); four respondents came from local government, an executive agency or civil society, and one entry could not be classified. Sixteen respondents answered the open question on a data-informed decision.

Table 15. Full distribution of closed-question responses in the practitioner assessment (n = 22)

Item	Option	n	%
Perceived HR-data maturity (single response)	Reporting	8	36.4
	Monitoring	3	13.6
	Decision-making	6	27.3
	Performance management	5	22.7
Barriers (multiple responses)	Lack of HR analytics skills	14	63.6
	Weak linkage between HR and organisational strategy	14	63.6
	Too much focus on reporting	12	54.5
	Limited M&E or evaluation skills	10	45.5
	Fragmented HR data across systems	9	40.9
	Poor data quality	9	40.9
	Lack of clear performance indicators	9	40.9
	Difficulty measuring outcomes and impact	9	40.9
Potential AI uses (multiple responses)	Skills-gap analysis	17	77.3
	Workforce forecasting	16	72.7
	Productivity analysis	14	63.6
	Employee performance analysis	12	54.5
	Employee engagement analysis	11	50.0
	Recruitment analytics	10	45.5
AI risks (multiple responses)	Data privacy	16	72.7
	Cybersecurity risks	12	54.5
	Poor-quality data producing misleading results	10	45.5
	Lack of human oversight	10	45.5
	Ethical concerns	9	40.9
	Lack of transparency or explainability	7	31.8

Item	Option	n	%
Governance attitudes (agree or strongly agree)	Clear policies and guidelines are needed before scaling AI in HR analytics	20	90.9
	AI-generated insights should always be subject to human review	19	86.4
	My organisation currently has adequate safeguards (moderate: 7; disagree or strongly disagree: 5)	10	45.5

Note. Results are descriptive and exploratory. The sample is not representative, and multi-select percentages do not sum to 100 per cent. Percentages are of 22 respondents.

Open-ended themes. Recurring issues in the open responses were a weak connection between HR indicators and institutional results, limited analytical skills and data interpretation, connectivity and information sharing between systems, deployment, and the difficulty of demonstrating outcomes. Examples of decisions informed by HR data included recruitment delays prompting talent pools, staff shortages informing recruitment, training-needs information, turnover data feeding succession planning, staff deployment, the identification of performance gaps and the use of the public employee performance management information system.