2026 Ibrahim Index of African Governance

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Methodology

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Methodology

INTRODUCTION TO THE IIAG

The Ibrahim Index of African Governance (IIAG) provides a biennial statistical assessment of governance performance in 54 African countries.

Data from diverse sources are combined into composite governance scores – an *Overall Governance* score, categories, sub-categories, clustered indicators, as well as clustered sub-indicators. The 2026 IIAG provides comparable data for the ten-year time period 2016-2025 enabling analysis of national and regional trends over time.

This document contains a detailed explanation of how the IIAG is calculated. The methodology is simple and transparent. All of the underlying data and information used in the construction of the IIAG are freely available and transparently published by the Mo Ibrahim Foundation (MIF), alongside the scores and uncertainty estimates. Given the impossibility to directly observe the nature of governance, all measures are made with error and users of the Index are encouraged to use the confidence intervals when interpreting the scores. This document will outline how MIF conceptualises governance, assumptions made, how variables are selected for inclusion, how the IIAG is calculated and how we estimate uncertainty around the scores.

MEASURING GOVERNANCE

MIF defines governance as the provision of the political, social, economic and environmental goods and services that every citizen has the right to expect from their state, and that a state has the responsibility to deliver to its citizens. The IIAG is concerned with operationalising these public goods mostly through outputs and outcomes of policy, as opposed to inputs or de jure indicators. Although the latter are selected in occasions when suitable output or outcome variables are not available. The framework of the IIAG has been constructed to reflect this definition and consists of four main pillars of governance: *Security & Rule of Law*; *Participation, Rights & Inclusion*; *Foundations for Economic Opportunity* and *Human Development*. These categories are comprised of 16 sub-categories. The structure of the 2026 IIAG (to sub-category level) can be seen in Table 1 below.

Table 1. 2026 IIAG framework (to sub-category level)

OVERALL GOVERNANCE			
SECURITY & RULE OF LAW	**PARTICIPATION, RIGHTS & INCLUSION**	**FOUNDATIONS FOR ECONOMIC OPPORTUNITY**	**HUMAN DEVELOPMENT**
Security & Safety	Participation	Public Administration	Health
Rule of Law & Justice	Rights	Business & Labour Environment	Education
Accountability & Transparency	Inclusion & Equality	Infrastructure	Social Protection & Welfare
Anti-Corruption	Women's Equality	Rural Economy	Sustainable Environment

Each construct is operationalised as a composite indicator of its sub-components. The *Overall Governance* score is constructed by calculating an average of its underlying four categories; these categories are constructed by calculating an average of their respective sub-categories. Likewise, sub-category scores are the result of aggregating the scores of their underlying indicators. There are 96 indicators in the 2026 IIAG, 90 of which are clustered and six are standalone indicators. Indicators are formed by variables. A variable is anything that can be constituted as a raw data from source. There are 319 variables collected to calculate the 2026 IIAG. In total, the 2026 Index contains 489 measures of governance (taking into account the variables collected from source as well as every composite score provided in the IIAG dataset).

The underlying 319 Index variables draw on a mix of quantitative measures and numerically coded qualitative assessments, collected from 51 African and international data sources. Quantitative measures capture directly observable outcomes, such as *Pupil-Qualified Teacher Ratio in Primary Education*. Other variables translate qualitative evidence into numerical scores, e.g. expert assessments of *Access to Justice* based on defined criteria and supported by contextual analysis. Combining these different types of evidence allows the IIAG to capture aspects of governance that are inherently more difficult to quantify, such as the quality, effectiveness or implementation of institutions and policies.

TECHNICAL ASSUMPTIONS

The central assumption is that each indicator score is the true value of its respective sub-category score plus or minus some error. Each constituent indicator measures something specific – for example *Education Enrolment* – but when included in a sub-category together with other indicators, it is expected to measure a broader concept; in this case whether a country has a comprehensive education system. In some countries which have high education enrolment rates, completion rates may be a lot lower because of the lack of adequate support systems for students at risk of dropping out, and therefore enrolment rates may overestimate the adequacy of education provided in a country. It is this misestimation which is captured in the error term, as discussed further in the section on uncertainty estimates.

The IIAG makes the assumption of independence across indicator errors. This is illustrated in the *Civil Registration* and *Budgetary & Financial Management* indicators from the *Public Administration* sub-category. Both indicators misestimate *Public Administration* by some amount, but because the indicators come from different sources – in the case of *Civil Registration*: from the Africa Integrity Indicators from the African Institute for Development Policy; in the case of *Budgetary & Financial Management*: from the Country Policy and Institutional Assessments from the African Development Bank and the World Bank – there is no reason to suppose that when one indicator misestimates *Public Administration* the other indicator will do the same. It is assumed that the errors are not related and will cancel each other out when the indicators are aggregated. The more indicators are added the more likely it is that the errors sum to zero. Any correlation between indicators arises as a result of a latent governance dimension. This misestimation is elaborated in greater detail in the section on uncertainty estimates.

VARIABLE SELECTION & CRITERIA FOR INCLUSION

To be included in the IIAG, a variable has to be linked to MIF's definition of governance and should preferably measure outputs and outcomes of governance, not inputs or *de jure* measures. For example, to measure the level of education in a country, the indicator *Education Quality* is used, as opposed to expenditures made by a government on education. Further considerations around inclusion of a variable include its methodological soundness, timeliness and accessibility, as well as the credibility of the data provider.

For each dataset under consideration, missing data is a large issue. In particular, the number of African countries covered by each dataset in a certain year, the number of years covered, the periodicity of the data and the most recent year of published data are all parameters which impact the precision of the composite scores.

Furthermore, comparability across countries and over time is fundamental. Data should be based on common concepts, definitions, classifications, and methodology. For this reason, data collected nationally (e.g. by a government agency) which are not internationally comparable cannot be used.

Given these considerations, to be included in the IIAG, a variable must have at least two years' worth of data since the beginning of the time series (2016 in the case of the 2026 IIAG dataset, these two data points must be distinct, and the latest data point must exist within the last three years (2023-2025 in the case of the 2026 IIAG dataset). These conditions must be met for 33 African countries. Furthermore, all selected variables exist on a five-point scale or higher to ensure numerical granularity and differentiate meaningfully between country scores.

When a variable is deemed to be suitable for inclusion, it is assigned to the sub-category in which it sits best conceptually. As dimensions of governance are not independent and variables may be deemed to be suitable for multiple sub-categories, this process goes through an additional stage of consultation with the IIAG Expert Panel, a group of expert advisors.

Following advice from the European Commission's Competence Centre on Composite Indicators and Scoreboards (CC-COIN), some additional guiding principles when selecting variables for the 2026 IIAG framework were the following:

- Missingness: The percentage of values missing from a variable should not overcome 20% in a year. Minimising the amount of missing values leads to a lower proportion of imputed data points and helps ensure that country sub-category scores are not dependent on a single variable.
- Correlation structure: The level of correlation for every variable/indicator should be higher than 0.3 with every level of the index (variables, sub-indicators, indicators, sub-categories, categories, Index).
- Correlation structure: There should be no cases of low correlation between variable/indicator and higher levels of the Index.
- Correlation structure: There should be no cases of redundant variables/indicators and/or highly correlated with every level of the Index that are of no added value for the overall Index.
- Principal Component Analysis (PCA): The percentage of variance explained by the first principal component should be ideally higher or equal to 70%. In cases failing this, alternate frameworks were trialed to maximise the result while maintaining conceptual coherence.

In Annex 1, a full variable selection tree is provided.

OUTLIERS & TREATMENT

In some instances, a variable includes observations which lie far away from the mass of the rest of the distribution. Including these extreme observations in the IIAG would bias the measure scores as, after normalisation, the outliers would make the range skewed and differentiation between most of the countries' scores would be difficult. To prevent this, the raw data is analysed to determine whether any of the variables require treatment to address outliers.

MIF uses a lopsidedness approach designed to identify variables with unusually long tails relative to the main body of the distribution. The method evaluates both the magnitude and length of the right and le tails using quartiles, the interquartile range (IQR) and the median. Tail lengths are calculated as the ratio between the maximum or minimum and the median over the IQR. Tail volumes are calculated as the ratio between the top and bottom quartiles over the rest of the distribution:

$$\text{Right tail length} = \frac{\text{maximum - median}}{\text{IQR}}$$

$$\text{Left tail length} = \frac{\text{median - minimum}}{\text{IQR}}$$

$$\text{Right tail volume} = \frac{\text{maximum - 3}^{\text{rd}}\text{ quartile}}{\text{3}^{\text{rd}}\text{ quartile - minimum}}$$

$$\text{Left tail volume} = \frac{\text{1}^{\text{st}}\text{ quartile - minimum}}{\text{maximum - 1}^{\text{st}}\text{ quartile}}$$

A variable is flagged as containing outliers when:

$$\text{Right tail length} > 10 \text{ AND } \text{Right tail volume} > 5 \text{ OR}$$
$$\text{Left tail length} > 10 \text{ AND } \text{Left tail volume} > 5$$

In the 2026 IIAG, 13 variables were treated for outliers: *Absence of Violent Events in State-Based Conflicts*, *Absence of Violent Events in Non-State Conflict*, *Absence of Government Violence against Civilians*, *Absence of Non-State Actor Violence against Civilians*, *Absence of Refugees*, *Internet Speed*, *Cost of Broadband Internet*, *Internet Security*, *Pupil-Qualified Teacher Ratio in Primary Education*, *Affordable Urban Housing*, *Sustainable Agriculture*, *Control of Primary Forest Loss* and *Marine Protected Areas*.

Of these 13, six variables *(Absence of Violent Events in State-Based Conflicts*, *Absence of Violent Events in Non-State Conflict*, *Absence of Government Violence against Civilians*, *Absence of Non-State Actor Violence against Civilians*, *Internet Speed* and *Pupil-Qualified Teacher Ratio)* were treated using square root power transformation with a factor of 1/2. One variable *(Absence of Refugees)* was treated using cube root power transformation with a factor of 1/3. These factors were chosen because they were the mildest of the common factors used in power transformation (1/2, 1/3, 1/4, 0, 2) which made the variables in question pass the tail outlier test.

All other variables *(Cost of Broadband Internet, Internet Security*, *Affordable Urban Housing*, *Sustainable Agriculture*, *Control of Primary Forest Loss* and *Marine Protected Areas)* were treated according to the following scheme: The trimmed mean and trimmed standard deviation were computed on the central 95% of the distribution. All observations further than three trimmed standard deviations away from the trimmed mean were replaced with:

$$\text{Replacement value} = \text{Trimmed mean} \pm 3.1 * \text{Trimmed standard deviation}$$

DEALING WITH MISSING DATA

The majority of the variables included in the IIAG have a degree of missing data over the time series (2016-2025). To ensure continuity between composite scores over time, values for these years are imputed.

The imputation approach was selected following comparative testing of a range of methods, including mean substitution, regression-based and multilevel approaches, and different forms of interpolation and extrapolation. Tests in which observed data were temporarily removed and then re-estimated showed that linear interpolation provided the best balance of accuracy and precision for IIAG data, slightly outperforming mean substitution and producing more consistent estimates than more complex alternatives. Alongside its comparatively stronger performance, this approach has the advantage of being relatively simple, transparent and reproducible.

Linear interpolation is therefore used to estimate missing data in the interior of a time series. Missing values between available observations are replaced with values incrementally higher or lower than the neighbouring data points. For missing data points that are located in the exterior of a time series, the nearest available observation was deemed to be the best proxy. Hence, the exterior missing values are imputed using the closest data point from source — last value carried forward (LVCF) or first value carried backward (FVCB).

As an example, Country A has data missing for years 2016, 2019 and 2020. The second row of Table 2 contains raw data. For the interior missing values in years 2019 and 2020, linear interpolation is used to obtain the value, as shown in the third row of Table 2. For the exterior missing value in year 2016, the missing data is imputed using FVCB to obtain the data as shown in the fourth row.

Table 2. Imputation example for Country A

Year	2016	2017	2018	2019	2020	2021
Raw data from source		85.1	84.8			82.8
Between data points		85.1	84.8	*84.1*	*83.5*	82.8
Outside data points	*85.1*	85.1	84.8	*84.1*	*83.5*	82.8

Let x be the raw data value of a variable for a country in year t. If there is no data for year t_2, and there are data for the years t_1 and t_3, whereby t_1 and t_3 are the closest years to t_2 such that $t_1<t_2<t_3$, linear interpolation can be illustrated as follows:

$$x_2 = x_1 + (t_2 - t_1) * \frac{(x_3 - x_1)}{(t_3 - t_1)}$$

Using the above formula in the previous example, a missing value in 2019 would be imputed as follows using linear interpolation:

$$84.1 = 84.8 + (2019 - 2018) * \frac{(82.8 - 84.8)}{(2021 - 2018)}$$

Exceptions

Linear interpolation is only applied where there is sufficient source data to provide a reasonable basis for estimation. Where no source data is available for a country across the full time series of a variable, no imputation is carried out. Where only one observation is available, the country-variable series is excluded, as linear interpolation requires at least two observed values and carrying a single value forward and backward would effectively assume no change over time without supporting evidence. Hence, the IIAG variable inclusion criteria of requiring at least two observations helps reduce the risk of inaccurate or misleading estimates.

NORMALISATION

Data used in the construction of the IIAG are diverse and include both quantitative and qualitative assessments provided by a range of data providers. At source, the variables collected are produced on different scales and can also have different polarities (e.g. in raw data terms, while for *Private Property Rights* a higher score is better, for *Absence of Government Violence against Civilians* a higher score is worse). In order for them to be meaningfully combined and compared, raw data is standardised before being included in the IIAG.

The data points for each variable are transformed using the min-max normalisation method. This method performs an order-preserving linear transformation of the data, in which the maximum value in the raw data becomes the highest score and the minimum value in the raw data becomes the lowest score for each variable.

The min-max normalisation method subtracts from the actual value the minimum value of the entire raw dataset (2016-2025) in the specific variable and divides by the range of the variable values. The scores for each country's value in a particular year, where the polarity of the raw data is 'higher value is better', are transformed as follows:

$$x = 100 * \frac{\text{actual value} - \text{minimum raw value}}{\text{maximum raw value} - \text{minimum raw value}}$$

If the polarity of the raw data is 'higher value is worse', the scores must be inverted. Therefore, the previous formula must be altered as follows:

$$x = 100\text{-}100 * \frac{\text{actual value} - \text{minimum raw value}}{\text{maximum raw value} - \text{minimum raw value}}$$

This method of standardisation allows all scores to be published in common units and within the same bounds of 0.0-100.0, in which 100.0 reflects the best performance in Africa across the ten years. 100.0 does not imply perfect governance but indicates the best score in Africa according to the raw data. Thus, meaningful comparisons between variables and countries can be made. Other advantages of this method include preserving the skewness and kurtosis and not making any assumptions about the distribution of the data.

AGGREGATION & WEIGHTING

To aggregate underlying variables into clustered sub-indicators, indicators, sub-categories, categories and the overall Index, the IIAG uses arithmetic means, i.e. a higher measure is made up of the average of its underlying measures. The decision to weight the four overarching categories equally in the IIAG was taken based on the judgment that the four governance dimensions of the IIAG – *Security & Rule of Law*; *Participation, Rights & Inclusion*; *Foundations for Economic Opportunity* and *Human Development* — are of equal importance in measuring governance.

While the weight of the categories and sub-categories is equal in the *Overall Governance* composite score, indicators and underlying variables have different implicit weighting as a result of the structure of the IIIAG: The number of indicators per sub-category ranges from from four to seven, with the majority of sub-categories containing six indicators. This effectively means that each of the indicators of sub-categories such as *Sustainable Environment*, which only has five underlying indicators, contribute more to the *Overall Governance* score than those of sub-categories such as *Health*, which has seven underlying indicators.

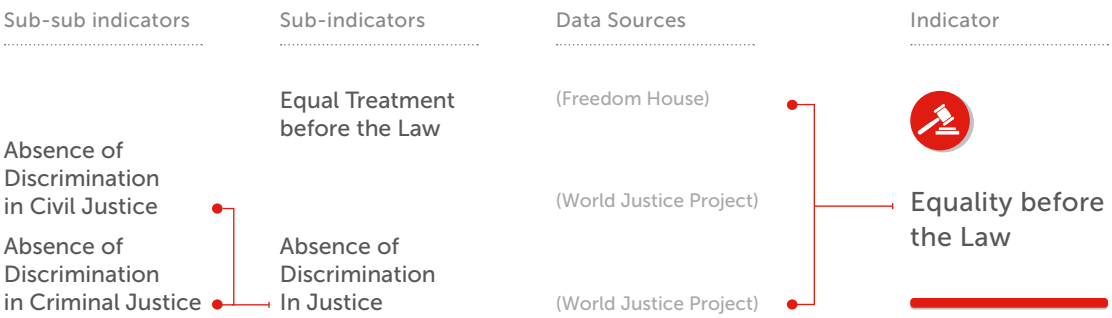
CLUSTERING

The underlying 319 variables included in the IIAG are constituents of 96 indicators, 90 of which are clustered indicators. A clustered indicator or a sub-indicator is composed of a number of underlying variables which capture the same dimension.

The data included in the IIAG comes from 51 different institutions and are a mix of quantitative and qualitative assessments. The diversity of sources and types of data means the measurement error in the composite values is minimised. A measure can be clustered as a result of similar variables being available from multiple sources or when different variables can be considered a proxy for the same wider concept.

For example, variables measuring narrow concepts such as *Absence of Discrimination in Civil Justice* and *Absence of Discrimination in Criminal Justice*, collected from the World Justice Project, are clustered together to create the *Absence of Discrimination in Justice* sub-indicator. In turn, this sub-indicator is clustered together with the sub-indicator *Equal Treatment before the Law*, collected from Freedom House, to create the indicator *Equality before the Law*, as seen below in Table 3.

Table 3. Clustering example for *Equality before the Law*



QUANTIFYING UNCERTAINTY

The Foundation publishes standard errors and confidence intervals alongside the *Overall Governance* and category scores to reflect degrees of uncertainty. The standard errors and confidence intervals allow users of the IIAG to discriminate, to a certain degree, between changes in the values of the IIAG that can be confidently treated as actual changes in the state of governance and changes that might be due to "noise", or are at least insufficiently sizeable to be able to ascribe a high likelihood to such change being statistically significant. Users of the IIAG are encouraged to use these to interpret changes in country scores over time and differences between country scores. For example, score or rank comparisons between countries with overlapping confidence intervals should generally be avoided as they represent a statistical tie. Similarly, users are encouraged not to over interpret marginal differences in a country's score change and refer to the confidence intervals for statistically significant movements.

Standard errors

For previous IIAG iterations, the method that has been used to calculate the standard errors was based on a process called *Bootstrapping*. It relies on creating multiple new versions of the dataset, by replacing values of measures with other values from the dataset (allowing for duplicates). It is a very common method and has the advantage of not making assumptions on the distribution of the data.

Bootstrapping, however, has been criticised. The bootstrap process is done at the sub-category level. Consequently, it will only have up to seven indicator values (or fewer for different sub-categories or when data is missing) to bootstrap from, which is likely to produce standard errors that will underestimate the true standard deviation of the scores.

Another issue with bootstrapping is its lack of replicability because of the random nature of the selection of values for the creation of resampled datasets. As such if an external party were to calculate the standard errors themselves, even if they followed the methodology to write their own bootstrapping algorithm, they would not be able to arrive at the same results.

Additionally, since bootstrapping is done with replacement, in the presence of missing values, the resampled datasets may not have the same amount and/or the same positions of missingness as the original dataset, which could also lead to incorrect estimating of the true standard errors.

The MIF Research Team has worked with Prof. Ali Hadi, a longstanding member of the IIAG Expert Panel, to implement a new standard error calculation method, which solves some of the issues related to bootstrapping. The new method is theoretically-based and replicable (that is, it does not depend on the re-sampling methodologies as does the Bootstrap). Since it is given in a closed-form equation, it drastically cuts down the time needed for the programme to run. Additionally, the resultant standard errors are more accurate than those provided by the Bootstrap.

Theoretically, the computations of the standard errors of the index or sub-index depend on what assumption one is willing to make about the covariance matrix of the index data. If $x = (x_1, x_2, \cdots, x_d)$ represents *d* variables or indictors in a sub-category or a category of the index data. For example, a simplifying assumption is that the variables for country *i* in year *t* are uncorrelated and have possibly different variances, which depend on both country *i* and year *t*. A justification of this assumption is that the data comes from different sources. But since they are measurements of basically the same underlying concept, they should be correlated. Under this assumption, however, the standard error of the index for country *i* in year *t*, y_{it}, can be estimated by:

$$SE(y_{it}) = \frac{s_{it}}{\sqrt{d}} \qquad i = 1, 2, \cdots, n, \qquad t = 1, 2, \cdots T$$

from which a $(1 - \alpha)$ 100% confidence bands for $E(y_{it})$ can be computed as:

$$[y_{it} \pm z_{\alpha/2} SE(y_{it})] \qquad i = 1, \cdots, n, \qquad t = 1, \cdots, T$$

Confidence intervals

Standard errors are used to construct confidence intervals across all higher-level composite measures of the Index (*Overall Governance*, the four categories and the 16 sub-categories). Four different degrees of confidence are available across all MIF IIAG publications: 80%, 85%, 90% and 95%). Confidence intervals are calculated using the critical values (Z-scores) from the standard normal distribution, whereby for 80% Z=1.282, for 85% Z=1.440, for 90% Z=1.645 and for 95% Z=1.960.

$$x_2 = x_1 \pm Z * \text{standard error}$$

READING THE RESULTS

Historical revision

The IIAG is refined and revised on a biennial basis to continually improve its measurement of governance. Improvements are a result of either methodological changes, or based on the inclusion of new data. Equally, if previously included measures undergo fundamental methodological changes or do not meet the criteria for inclusion it may be necessary to exclude them from future iterations. It is also necessary to update previously published data if retrospective revisions are made to data at source.

As a result of these changes, the IIAG is collected and re-calculated every two years for the last decade (in the case of the 2026 IIAG that is 2016-2025). The retrospective revision means that **no previous publications should be compared to the 2026 IIAG scores** as differences may be a result of a change in framework or an update in data from source rather than due to a change in score. **Score and rank comparisons between years should be made entirely within the 2026 IIAG.**

Relativity

The IIAG country scores and ranks are all relative, taking into account a country's performance in relation to the other 54 African countries. This is a result of the normalisation procedure, which transforms the raw data into a scale of 0.0-100.0, whereby 100.0 is the best score. This means that a country's change in score and rank may be reflective of other countries performing better or worse. Users of the IIAG are encouraged to treat marginal differences in scores and ranks with caution and refer to the standard errors for statistically significant changes.

Scores, ranks, changes and trends

Four main criteria can be used to analyse the performance of a country or a governance measure: latest year score, latest year rank, change over the past decade and trend over that decade. Rounded to one decimal point in all final IIAG datasets and analyses, scores quantify a country's performance for each governance measure for each data year, expressed out of 100.0 (with 100.0 being the best score). Ranks are calculated based on the respective scores and are expressed out of 54. When two or more countries have the same score, they share the same place in the ranking table (tied ranks). For the average scores of Regional Economic Communities (RECs), ranks are expressed out of eight. Ten-year changes quantify the difference in score between the last and the first data years of the decade under review. The 2026 IIAG ten-year changes compare the country's performance reached in 2025 to the one reached in 2016.

Trends are a fourth layer of analysis, complementing scores, ranks and ten-year changes. The IIAG trends serve to assess the trajectory of a country or governance measure over the decade, by comparing the average rate of change over the latest five years (2021-2025) to that of the full decade (2016-2025). This comparison helps identify early signs of the direction and pace of country trajectories. Table 4 below gives an overview of the IIAG trends and characteristics.

Table 4: 2026 IIAG trends and characteristics

Trend	Characteristic
Increasing Improvement	Score is better in 2025 compared to 2016, with the rate of improvement increasing since 2021.
Slowing Improvement	Score is better in 2025 compared to 2016, but the rate of improvement is slowing since 2021.
Warning Signs	Score is better/no change in 2025 compared to 2016, but showing decline since 2021.
Bouncing Back	Score is worse/no change in 2025 compared to 2016, but showing progress since 2021.
Slowing Deterioration	Score is worse in 2025 compared to 2016, but the rate of deterioration is slowing since 2021.
Increasing Deterioration	Score is worse in 2025 compared to 2016, with the rate of deterioration increasing since 2021.
No Change	Score has not changed at all over the decade 2016-2025.
Not Classified	Data is missing so trend cannot be assessed.

Trends are determined by comparing year-on-year average changes over the whole series (2016-2025) and over the last half of the decade (2021-2025). These ten-year annual average trends (AAT10) and five-year annual average trend (AAT5) are calculated by dividing the score difference by the number of years over which it took place:

$$AAT10 = \frac{Score_{2025} - Score_{2016}}{9} \qquad AAT5 = \frac{Score_{2025} - Score_{2021}}{4}$$

To assign the trends, the following criteria are used:

Increasing Improvement	=	$AAT10 > 0$ AND $AAT5 > 0$ AND $AAT10 < AAT5$
Slowing Improvement	=	$AAT10 > 0$ AND $AAT5 > 0$ AND $AAT10 > AAT5$ OR $Score_{2025} = 100$ AND $Score_{2021} = 100$ AND $AAT10 > 0$
Warning Signs	=	$AAT10 > 0$ AND $AAT5 < 0$ OR $AAT10 = 0$ AND $AAT5 < 0$ OR $AAT10 > 0$ AND $AAT5 = 0$
Bouncing Back	=	$AAT10 < 0$ AND $AAT5 > 0$ OR $AAT10 < 0$ AND $AAT5 = 0$ OR $AAT10 = 0$ AND $AAT5 > 0$
Slowing Deterioration	=	$AAT10 < 0$ AND $AAT5 < 0$ AND $AAT10 < AAT5$ OR $Score_{2025} = 0$ AND $Score_{2021} = 0$ AND $AAT10 < 0$
Increasing Deterioration	=	$AAT10 < 0$ AND $AAT5 < 0$ AND $AAT10 > AAT5$
No Change	=	$AAT10 = 0$ AND $AAT5 = 0$
Not Classified	=	scores 2016 - 2021 = n/a

In the rare instances that AAT10 and AAT5 are exactly the same, MIF classifies them as *Steady Improvement* or *Steady Deterioration*:

Steady Improvement	=	$AAT10 > 0$ AND $AAT5 > 0$ AND $AAT10 = AAT5$
Steady Deterioration	=	$AAT10 < 0$ AND $AAT5 < 0$ AND $AAT10 = AAT5$

Annex: Variable selection tree

A. Conceptual framework

1. Is the variable linked to MIF's definition of governance?

- Yes, the concept is defined in a way that captures the governance aspect. When "proxy" series are used, there needs to be evidence of their relationship with "target" series.
- No, the concept is not defined in a way that captures the governance aspect.

2. Does this variable measure an input or outcome of governance?

- It preferably focuses on outcomes of governance (e.g. level of quality in education).
- It focuses on inputs of governance (e.g. laws or expenditure levels).

B. Data availability and methods

3. What are the data provider/source and its methods?

- Widely credible data source and the methods it uses are sound. Data is perceived to be objective, produced professionally in accordance with appropriate statistical standards and policies and practices are transparent.
- Not credible data source, using unknown, biased methods, or lacks rigorous data collection.

4. Is the data coherent/comparable?

- Yes, coherence/comparability over time and across countries can be ensured. Data is based on common concepts, definitions, classifications, and methodology, and any differences are explained and can be accounted for.
- No, coherence/comparability over time and across countries cannot be ensured. Incoherence over time refers to breaks in a series resulting from changes in concepts, definitions, or methodology. Data collected nationally (e.g. by a government agency) which is not internationally comparable cannot be used.

5. Can we expect the variable to be discontinued any time soon?

- No, the source plans to keep producing the data, maintaining its operationalisation/methodology.
- Yes, the source plans to stop producing the data, or change its operationaliation/methodology.

6. What is the country coverage?

- It covers at least 33 African countries.
- It covers fewer than 33 African countries.

7. How many data points are there at the country level?

- There are at least 33 African countries with two distinct data points from source since the beginning of the time series (2016 in the case of the 2026 IIAG dataset).
- There are fewer than 33 African countries with two data points from source since the beginning of the time series (2016 in the case of the 2026 IIAG dataset).

8. How old is the latest data point at the country level?

There are at least 33 African countries whose latest data point is no more than three years old (2023-2025 in the case of the 2026 IIAG dataset).

There are fewer than 33 African countries whose latest data point is no more than three years old (2023-2025 in the case of the 2026 IIAG dataset).

9. What is the level of missingness? (Data coverage)

The percentage of values missing from a variable does not overcome 20% in a year.

The percentage of values missing from a variable overcomes 20% in a year.

10. What is the numerical granularity of the variable's raw data?

Raw data from source comes on a four-point scale or more, which is essential to meaningfully distinguish country performance.

Raw data from source comes on less than a four-point scale.

C. Statistical/internal structure

11. How does the variable correlate with other components/levels?

The variable has a correlation coefficient higher than 0.30 with every level of the index (variables, sub-indicators, indicators, sub-categories, categories, index).

The variable has a correlation lower than 0.30 or is negatively correlated with higher levels of the index (the indicator, sub-category or category in which the variable sits).
The variable is redundant and/or highly correlated with every level of the index (other components at the same level, as well as higher levels of the index).

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