‘National IQ’ datasets do not provide accurate, unbiased or comparable measures of cognitive ability worldwide

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Abstract
In 2002, Lynn and Vanhanen produced a dataset which claimed to provide average ‘national IQs’ for nation-states worldwide. Despite extensive critique, this dataset, and subsequent updated versions, have been used in a large number of empirical publications. Here I evaluate the latest version, produced in 2019 by Lynn and Becker, and show that this dataset is not fit for purpose. The primary data sources are inadequate for estimating ‘national IQs’. The majority of data included originates from samples which are wholly unrepresentative of their national populations. Many are convenience samples with small sample sizes, often including only children and often including individuals chosen because they had particular characteristics (i.e., samples which were deliberately chosen to be unrepresentative). Data were collected using a range of different cognitive tests and from such diverse populations that it is impossible to generate comparable measure of cognitive ability. There is also evidence that further bias may have been introduced during manipulations of primary data into ‘IQ’ scores. The extent of these biases differs by world region, meaning that the dataset is not only inaccurate but systematically biased. This ‘national IQ’ dataset therefore does not provide comparable, accurate and unbiased measures of cognitive ability worldwide, and should not be used be draw inferences about global variation in intelligence.

The 'national IQ' datasets

In 2002, Richard Lynn and Tatu Vanhanen produced a dataset which purports to provide an average 'national IQ' for 185 nations worldwide (Lynn & Vanhanen, 2002). This dataset was based on 'measured IQs' for 81 nations, and estimated IQs, extrapolated from 'measured IQs', for the remaining 104 countries. 'Measured IQs' were estimated from a diverse range of previously published primary data sources, which collected data on cognitive ability from individuals. Primary data were typically subject to various transformations in order to calculate an 'average IQ' for each nation state. The dataset was subsequently updated by Lynn and Vanhanen in 2006 (Lynn & Vanhanen, 2006) and 2012 (Lynn & Vanhanen, 2012); then Lynn collaborated with David Becker to provide a further update in 2019 (Lynn & Becker, 2019). This 2019 version of the dataset provides 'measured IQ' for 131 countries, and extrapolated IQs for a further 72, and is available online[1] (latest version 1.3.3, dated June 2019).

These datasets have been extensively used by Lynn and colleagues, and many other researchers, in empirical analyses which have correlated cognitive ability with a wide range of other variables (Figueredo, Hertler, & Peñaherrera-Aguirre, 2020; Kanazawa, 2006; Lynn, 2006; Lynn & Becker, 2019; Lynn & Vanhanen, 2002, 2006; Templer & Arikawa, 2006). Such research is often used to draw conclusions about the causal effects of cognitive ability on global variation in other outcomes. For example, Lynn and Vanhanen have used the dataset to claim that global variation in wealth can be attributed to variation in intelligence between different world regions (Lynn and Vanhanen, 2002, 2006). Kanazawa (2006) has used the dataset to claim that mortality rates are higher in low-resource countries not because of lack of access to resources but because of lower average intelligence in these countries.

Such dramatic claims require an extremely strong evidence base and rigorous methods, yet the 'national IQ' datasets have been extensively criticised on multiple grounds, including cherry-picking of evidence and inadequate primary data sources (Barnett & Williams, 2004; Dickins, Sear, & Wells, 2007; Ervik, 2003; Kamin, 2006; Richardson, 2004; Volken, 2003; Wicherts, Borsboom, & Dolan, 2010). Despite extensive documentation of methodological flaws, in their book published alongside the 2019 version of the dataset, *The Intelligence of Nations*, Lynn and Becker consider the dataset to have achieved *'mainstream acceptance'* (Lynn & Becker, 2019, p10), and these 'national IQ' data are still being used in empirical research (Achim et al, 2021; Figueredo et al, 2021).

Here I provide a thorough evaluation of the 2019 version of the 'national IQ' dataset, having previously critiqued the 2006 version (Dickins, Sear & Wells, 2007). This evaluation comes to the same conclusions as existing critiques of previous versions of the dataset, and one other evaluation of the 2019 version (Ebbesen, 2020).

Evaluation of the 'national IQ' dataset

I evaluate the dataset by considering its potential to provide comparative, accurate and unbiased measures of intelligence worldwide, focusing particularly on the quality and suitability of the samples included. This evaluation involved:

- examining the dataset itself, including the secondary data Lynn and Becker collated and published alongside their calculations of 'national IQ' (discussed in Lynn and Becker, 2019, and the website associated with this version[1]). This secondary data constitutes Lynn and

[1] https://viewoniq.org/?page_id=9

Becker's assessments of various characteristics of the samples used to calculate 'national IQ' (which they refer to as *'secondary information or data'*).

- examining the methodology described in Lynn & Becker's 2019 book *'The Intelligence of Nations'*, which provides details of the construction of the dataset, with further updates provided on the dataset website.
- by consulting the primary sources for the samples included in the calculation of 'national IQ' scores for the region of sub-Saharan Africa (chosen because of the implausibly low scores for this region).

Summarising the dataset

Table 1 presents summaries of the data included in the 2019 dataset, by world region, to illustrate the nature of the samples used. This table only includes those countries for which data was available to 'measure' IQ, and not those countries where IQs were estimated based on data from nearby countries. This table immediately raises concerns about the dataset, as it implies some remarkable conclusions about global variation in IQ. In particular, the average IQ of sub-Saharan Africa is calculated to be 70. IQs below ~70-75 are considered to indicate intellectual disability (American Psychological Association, 2013) and it is wholly implausible that an entire world region should, on average, be on the verge of intellectual impairment. Table 1 also illustrates that 'national IQs' are mostly estimated from small sample sizes, mostly from samples of children, and that the dataset is biased, with sample sizes and ages of participants varying by world region.

The next sections considers the following questions: (1) How accurately do the samples included represent national IQ?; (2) Is there evidence that the dataset has been constructed transparently and without bias?; and finally (3) Is the same underlying construct being measured cross-nationally?

Table 1: summaries of data included in the 2019 'national IQ' dataset, by world region (as defined by the World Bank[2])

World region	Average IQ[3]	No. countries	% national IQs estimated from a single sample[4]	% national IQs estimated from sample sizes <1000/<5000	% national IQs estimated from samples <18 yrs	Mean age (range) of samples
Sub-Saharan Africa	70	25	40	48/88	72	13.0 (5-35)
East Asia & Pacific	94	17	10	29/65	65	12.8 (3-51)
South Asia	76	5	0	20/40	60	19.9 (5-67)
Europe & Central Asia	93	39	27	38/79	47	16.8 (5-67)
Middle East & North Africa	81	20	13	10/55	70	13.6 (5-29)
Latin America	81	23	10	56/83	74	13.3 (3-71)
North America	91	2	0	0/50	50	14.2 (3-45)
Total	*84*	*131*	*30*	*37/74*	*63*	*14.3 (3-71)*

[2] https://data.worldbank.org/country
[3] average IQs for 'world regions' are my own calculations based on the 'raw IQs' calculated before any adjustments (UW column in the NAT worksheet). Note that in version 1.3.3 of the 2019 dataset, IQs scores which were previously estimated to be <60 have been recoded to 60 in the UW column
[4] Summaries in the last 4 columns are calculated from Lynn and Becker's assessments of number of samples per country, sample size, sample age, which are included in the 2019 dataset

(1) How accurately do the samples included represent national IQ?

My evaluation of the 2019 dataset leads me to conclude that the primary data sources are inadequate for estimating 'national IQs', as the majority of samples are small and unrepresentative of national populations.

Table 1 shows that sample sizes are often small; 37% of all samples are under 1000 individuals, which are very small samples for calculating averages for national population, which may have many millions of citizens. Some samples are exceedingly small: a closer inspection of the dataset reveals that six countries have IQs estimated from <100 individuals (Angola's IQ is estimated from 19 individuals; Dominican Republic from 34; Greenland 40, Uzbekistan 51, Republic of Congo 88, "Netherlands Antilles"[5] 96) and a further 14 with samples of <200 (Namibia, Barbados, Sierra Leone, Ecuador, Ukraine, Botswana, Laos, Latvia, Costa Rica, Bolivia, Malta, Saint Vincent and the Grenadines, Haiti and Eritrea[6]). A significant proportion of countries – 30% – also have IQs estimated from a single sample, which is particularly problematic when so many samples are small and unrepresentative, including only children.

Table 1 shows that most countries appear to have IQs estimated only from children: almost two third of samples only include individuals under 18 years, and the majority of samples are biased towards younger individuals, as the mean age of samples in all world regions is younger than 20 years. This is problematic not only because these samples will be unrepresentative of the national population but also because psychometric test scores are affected by age (Garde, Mortensen, Krabbe, Rostrup, & Larsson, 2000; Mous et al., 2017).

Table 2[7] presents information on the representativeness of the samples included in the dataset, by world region. This information is based on Lynn & Becker's own assessment, and definitions, of sample type for each sample. They define 'national' populations as "*individuals originated from all or a large part of the country's total area which spans across more than only a single county, municipality, governmental area"*, p13). Alternatively, samples are defined as 'regional', 'urban, 'rural' or 'foreign' (*"the sample is from refugees or immigrants"*). According to the authors' own classification, only one third of the samples are 'national', meaning the other two thirds of samples cannot be assumed to accurately represent national populations[8]. Note also that 12 of the samples were not even collected in the country for which they were used to calculate 'national IQ' ('foreign' samples, mostly used to calculate 'national IQs' in sub-Saharan Africa or Latin America).

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[5] A country which was dissolved in 2010 but is still retained in the dataset; data come from Curaçao

[6] Note in the dataset, Lynn and Becker state a sample size for Eritrea of 764 but inspection of the primary sources suggests this appears to be based on (1) an error recording the sample sizes (2) recording the same children tested at different ages as independent samples

[7] Note that the summary presented in Table 2 includes only primary sources which administered psychometric tests. For some of their estimations of IQ, the authors include measures of student achievement, collected through TIMSS (Trends in International Mathematics and Science Study) and PIRLS (Progress in International Reading Literacy Study) surveys. These are surveys of student achievement conducted in many countries but not all, and excluding almost all countries in sub-Saharan Africa. These are not suitable for calculating 'national IQ' as they represent educational attainment, of children in school (so again not representative samples), and are not intended to be used as measures of national intelligence.

[8] An inspection of the primary sources also suggests Table 2 may overestimate the proportion of 'national' samples. For example, a sample of 74 orphans from a single orphanage in Eritrea is coded in the dataset as 'national'.

My examination of the primary sources from sub-Saharan Africa suggests that almost none come from studies which even attempted to sample a representative section of the national population. Some provide no information on sampling at all. The majority of those which do provide some information on the sample are convenience samples, meaning participants happened to be available for sampling, which are common in psychology. Many of the studies included were conducted to determine whether individuals with a particular characteristic (such as being a twin, having a health condition or a particular environmental exposure) had unusual cognitive test scores. Samples were therefore often selected by study authors because they had particular characteristics; in other words, they were deliberately chosen to be unrepresentative of the national population. For some samples, this 'treatment' group with a particular characteristic was excluded from the dataset, leaving only the 'control' group in the sample. But only including control groups does not result in nationally representative samples. Control groups are typically chosen to be as similar as possible to 'treatment' groups, apart from the exposure of interest, meaning they may come from specific locations within a country, from very narrow age ranges, or from specific ethnic groups. The few samples which were collected from reasonably representative samples typically have psychometric test scores available only for unrepresentative sub-samples, such as children of particular ages or from particular areas.

Some examples: the 'national IQ' of Angola is estimated from a single sample of 19 individuals about whom the only thing we know is that they did not have malaria; Eritrea's 'national IQ' is estimated entirely from small samples of children living in orphanages; Congo's 'national IQ' is estimated from one sample of 88 schoolchildren in their 6th year of schooling; Namibia's 'national IQ' is estimated from one sample of 103 children from an ethnic group which Lynn & Becker (2019, p116) acknowledge makes up only 7% of the population of that country. If we look in more detail at those 'foreign' samples: Somalia's 'national IQ' is estimated from one sample of child refugees in a Kenyan refugee camp; Botswana's 'national IQ' is estimated from one sample of 140 adolescents sampled in South Africa, and were apparently used to calculate the 'national IQ' of Botswana, not because there was evidence that there were from Botswana, but because they were from an ethnic group which is common in Botswana. These are just selected examples, but it is clear from examining the primary sources for sub-Saharan Africa and from Tables 1 and 2, that these sampling problems are widespread throughout the dataset.

Estimating 'national IQ' scores from such small, unrepresentative samples means the dataset contains considerable error. Despite sampling problems being common in all regions, it's also clear that sampling problems are more severe in some regions than others. This means the dataset will be systematically biased. Sub-Saharan Africa, for example, has a particularly high proportion of single-sample countries, of small sample sizes and samples including only children (Table 1). The authors of the dataset themselves demonstrate its biased nature (Lynn & Becker, 2019). In Chapter 2 of *The Intelligence of Nations,* the authors' analyse their data and demonstrate significant correlations between 'national IQs' and many sample characteristics, concluding: *"The analyses have shown that national IQs depend partly on characteristics of the samples on which they were measured"* [p201]. They show, for example, that samples had lower IQs if they had younger ages, were tested earlier in time, used older test norms and came from rural samples. Given the differences between regions in average sample characteristics shown in Tables 1 and 2, this means the dataset is regionally biased.

Table 2: Lynn & Becker's classification of sample types included in their dataset, by world region

Region		'National'	'Regional'	'Urban'	'Rural'	'Foreign'	unclassified[9]	No. samples
Sub-Saharan Africa	N	29	23	27	19	5	7	110
	%	26.4%	20.9%	24.5%	17.3%	4.5%	6.4%	
East Asia & Pacific	N	39	10	25	11	1	13	99
	%	39.4%	10.1%	25.3%	11.1%	1.0%	13.1%	
South Asia	N	11	3	12	18	0	2	46
	%	23.9%	6.5%	26.1%	39.1%	0.0%	4.3%	
Europe & Central Asia	N	58	26	46	0	1	13	144
	%	40.3%	18.1%	31.9%	0.0%	0.7%	9.0%	
Middle East & North Africa	N	33	9	31	6	1	4	84
	%	39.3%	10.7%	36.9%	7.1%	1.2%	4.8%	
Latin America	N	35	20	40	15	4	18	132
	%	26.5%	15.2%	30.3%	11.4%	3.0%	13.6%	
North America	N	18	22	21	1	0	6	68
	%	26.5%	32.4%	30.9%	1.5%	0.0%	8.8%	
Total	N	223	113	202	70	12	63	683
	%	32.7%	16.5%	29.6%	10.2%	1.8%	9.2%	

[9] Category labels were only provided for codes 1-5 in the online manual, though several samples were coded '6' in the spreadsheet

(2) Is there evidence the dataset has been constructed transparently and without bias?

a. No clearly stated methodology is provided to explain the authors' sampling of the literature

The authors include no clear methodology or search strategy for locating studies in the literature, nor are consistent inclusion or exclusion criteria stated. This is the only methodological description provided of the search and selection strategy: *"studies and reports of psychometric intelligence measurements from all around the world have been collected, selected according to suitability, corrected as necessary, and averaged for as many countries as possible"* (Lynn & Becker, 2019 p11). Clearly, choices were made about which studies to include and which to exclude (*"the inclusion criteria for this study [version of the dataset] has been stricter than that of its predecessors"*, p12), but without evidence that a systematic methodology for making inclusion/exclusion decisions was decided before data collection started, it is impossible to replicate the authors' strategy or to understand why they included some studies and not others. The absence of a clear, *a priori*, methodology does suggest bias may well have been introduced into the dataset during selection of studies to be included.

Previous critiques of the 'national IQ' dataset have provided evidence that there is bias in the way the dataset was constructed. Wicherts and colleagues' examination of the 2002 and 2006 datasets concluded that studies which found relatively high IQs for sub-Saharan Africa appear to have been systematically excluded (Wicherts, Dolan, Carlson, & van der Maas, 2010a; Wicherts, Dolan, & van der Maas, 2010a, 2010b). Wicherts and colleagues conducted their own systematic review of the literature on psychometric tests in sub-Saharan African populations, and used clearly stated inclusion criteria to select 11 studies for subsequent meta-analysis, studies they considered to be of reasonable quality (Wicherts, Dolan, & van der Maas, 2010a). Only 2 of these 11 studies are included in the 2019 'national IQ' dataset [10].

For those studies which were included in the dataset, decisions were also made about whether to include data from all individuals sampled in the study or only a subset. No *a prior* methodology is stated for inclusion or exclusion of sub-samples, but Lynn and Becker do provide some descriptions of how and why they excluded some sub-samples in their book (Lynn & Becker, 2019, Chapter 2). There appears to be no consistent rationale for these decisions. As described above, many of the studies included involve comparisons of two groups, and sometimes the 'treatment' group is excluded from the dataset, and only the 'control' group included, often partly justified on the grounds that the authors wanted only to include 'healthy' controls or to exclude particularly low scores. But sometimes the 'treatment' group is included, meaning that sometimes samples are included despite evidence of adverse health exposures. For example, a subsample of individuals diagnosed with malaria were excluded from the Angolan sample, but a subsample with malaria were included in a Ugandan sample. Malnourished children in Barbados, and children with a neuromotor disease (konzo) in the Democratic Republic of the Congo (DRC), were excluded; whereas in a different study in DRC, a subsample of children with attention deficit disorder were kept in the sample. In Ecuador, Pakistan, the Philippines, Serbia and Taiwan, samples of children exposed to lead were included, despite evidence that lead exposure may be associated with lower cognitive outcomes (Lanphear et al, 2000).

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[10] Of the 11 studies listed in Appendix A of Wicherts et al 2010a, only Buj 1981 and Skuy 2001 are included in Lynn & Becker 2019

The lack of any clearly stated methodology to guide decisions about which studies, and which sub-samples to include, mean that it is highly likely that this dataset was constructed on the basis of arbitrary and/or biased decisions. Note that concerns about sampling bias had been raised about previous versions of the dataset (Wicherts, Dolan, Carlson, & van der Maas, 2010a; Wicherts, Dolan, & van der Maas, 2010a, 2010b), but these concerns do not appear to have been addressed when constructing the 2019 version.

b. Assumptions used when transforming raw data from cognitive tests into 'national IQs' may have introduced further error and bias into the dataset

The primary data sources collected data using a range of different cognitive tests. Lynn and Becker (2019) report that data from 12 different types of cognitive tests are used to construct the dataset, with several tests having multiple sub-scales, only some of which may have been used in any study (p17, Table 4). This variability adds further error into the dataset, as the cognitive tests used in different studies may not be directly comparable.

Manipulations were then performed on data from these cognitive tests in order to translate them into 'IQ' scores. These are described in some detail in Lynn and Becker (2019), where the authors make clear that many assumptions were made when performing these transformations. This process has the potential to introduce yet more error and/or systematic bias in the dataset, and there is evidence that some bias may have been involved. For example, when transforming test scores from a study from the Gambia, the authors use a particular manipulation apparently based on an assumption that Gambians will not perform well on cognitive tests: *"no information was provided on which set(s) of the CPM* [Raven's Coloured Progressive Matrices, a psychometric test] *was or were used. If we assume that, because of the difficulty for people from countries like The Gambia to absolve* [sic] *cognitive tests like Raven's matrices and because the difficulty of Raven's items increases with their number-ranks, that the reported raw scores were mostly achieved on Set-A, we were able to calculate full CPM-raw scores of 18.99 and 23.19"* (Lynn & Becker, 2019, p80)[11].

(3) Is the same underlying construct being measured cross-nationally?

The comparability of 'national IQ' scores is already in serious question given the multiple different cognitive tests which were used to produce these scores, and the range of manipulations which were then applied to raw test data to calculate 'national IQs'. But it is highly unlikely that it is even conceptually possible to construct a meaningful, comparable measure of cognitive ability which measures the same underlying construct from diverse populations. Psychometric tests are culturally-specific, affected by education, by motivation, as well as a wide range of other environmental factors, and improve with coaching and on re-testing (Anum, 2014; Dramé & Ferguson, 2019;

[11] Lynn and Becker's calculation of the 'national IQ of the Gambia was 49.78/50.57 (*"weighted/unweighted"* p81) in the 1.3.1 version of the 2019 dataset described in Lynn and Becker (2019), which is on the borderline of 'moderate intellectual disability' (IQ range ~35-49). *"Persons with moderate ID function at mental age of about 6-8 years as adults"* (Patel, Cabral, Ho, & Merrick, 2020). In the latest version (Version 1.3.3), all 'national IQs' below 60 are given a 'corrected' value of 60, because of criticism the authors received about whether such low values were plausible (as described on the website associated with the 2019 version)

Duckworth, Quinn, Lynam, Loeber, & Stouthamer-Loeber, 2011; Kulik, Bangert-Drowns, & Kulik, 1984; Needleman & Gatsonis, 1990; Wicherts, Dolan, Carlson, & van der Maas, 2010b). Many of the studies included in the dataset provide clear evidence that the cognitive tests used are unsuitable for comparative work, and some include very clear statements that their samples should **not** be used for comparative purposes. Some studies were conducted with the explicit aim of exploring how cultural factors affect test scores, for example, and so provide evidence of the cultural specificity of these tests. The 'national IQ' of Mali is based on a single study in which the authors state, in their abstract: *"Results indicate that use of the Ravens may substantially underestimate the intelligence of children in Mali. This can be particularly problematic when comparisons are made across cultures using the same test and norms"* (Dramé & Ferguson, 2019). The authors of one study included for the Democratic Republic of the Congo (Boivin, Giordani, & Bornefeld, 1995) similarly state clearly in their abstract that results are not suitable for comparative purposes (similar statements can be found in: Alderman et al., 2014; Berry, 1966; Kaniel & Fisherman, 1991).

Authors of other studies included in the dataset describe how some children are disadvantaged in these tests. For example, a study which compared French children with those from the Congo stated in its methodology that *"The test situation…was much more familiar to the French students given their exposure to tests of knowledge in school"* (Nkaya, Huteau, & Bonnet, 1994). One Ethiopian sample is a rare example of data collected during a study designed to sample a broad section of the population (the Young Lives Survey) yet scores from only a subsample of children were available because *"Unfortunately in the Ethiopian version, administration of the test ran into difficulties relating to explanation of tasks & time constraints & only about a quarter of the sample—all urban children—have test scores available in the dataset"* (Dendir, 2013). These examples provide clear evidence that the same tests cannot be administered across very different settings and hope to produce comparable data.

The same cognitive tests cannot therefore be used to measure the same underlying construct of 'intelligence' cross-culturally. As with the sampling problems described above, the cross-cultural specificity of cognitive testing will introduce not just error into the dataset but systematic bias: for example, greater exposure to formal education is associated with higher scores (Brinch & Galloway, 2012; Matarazzo & Herman, 1984).

Implications

The multiple sources of error and bias in this dataset mean that any research which uses this dataset is unsound. Yet, this dataset has been used to draw conclusions about innate differences in intelligence between groups, particularly between races, and how these supposedly innate differences lead to a range of other economic, health and social outcomes (Figueredo, Hertler, & Peñaherrera-Aguirre, 2020; Kanazawa, 2006; Lynn, 2006; Lynn & Becker, 2019; Lynn & Vanhanen, 2002, 2006; Templer & Arikawa, 2006). Such claims have real world implications.

The authors of the dataset themselves draw explicit policy implications from these claims: Chapter 4 of *The Intelligence of Nations* is devoted to these implications, and the authors make five suggestions for *"strategies to increase national IQs"*. The fourth and fifth suggestions are *"positive eugenics; and negative eugenics"* (p318), and Lynn and Becker discuss a range of eugenic policies which have previously been used by governments, without any discussion of either the wholly flawed science or of the human rights violations which underly eugenic policies. Fortunately, they are pessimistic about the likelihood of implementing eugenic policies, concluding: *"The principal problem is the large number of highly educated high IQ career women who remain childless. It is probably impossible to introduce policies to increase the fertility of these women who have been educated out of their reproductive function. It is also probably impossible to introduce policies to reduce the fertility of those with low intelligence"* (p334). They also conclude that eugenic immigration policies – designed to reduce immigration from supposedly 'low IQ' to 'high IQ' countries – are likely to be ineffective (p334). However, it's not beyond the realms of possibility that this dataset may be used to draw conclusions about immigration policy in the US, given that a Harvard PhD dissertation drew on the 'national IQ' dataset to make recommendations about immigration policy (Richwine, 2009), written by an individual who subsequently took a government position (Mervis, 2020).

Conclusions

'National IQ' datasets do not provide comparable, accurate and unbiased data on cognitive abilities worldwide. A fundamental problem with these datasets is the wholly inadequate of the primary data sources which are used to build them. It is not that the primary sources are necessarily poor quality pieces of work themselves, but that they cannot be used to produce nationally-representative, globally comparative estimates of cognitive ability. The primary data typically come from small, unrepresentative samples, are generated from a number of different cognitive tests, and from such diverse populations that any attempt to generate globally comparative datasets of 'national IQ' is rendered meaningless. No amount of manipulation will make such primary data produce estimates which accurately reflect cross-national variation in cognitive ability. Nor is this dataset 'the best of bad job' which should be used until something better comes along. The way the dataset has been constructed means that it is systematically biased, and any empirical analyses which use the dataset will produce biased results.

It is very important that data and research which have significant real world consequences should be produced to the highest standards of methodological rigour. The nature of the biases in this particular dataset mean its use may lead to racist conclusions and legitimise eugenic arguments, even where that is not the intention of the authors. No future research should use this dataset, and published papers which have used the dataset should be corrected or retracted.

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