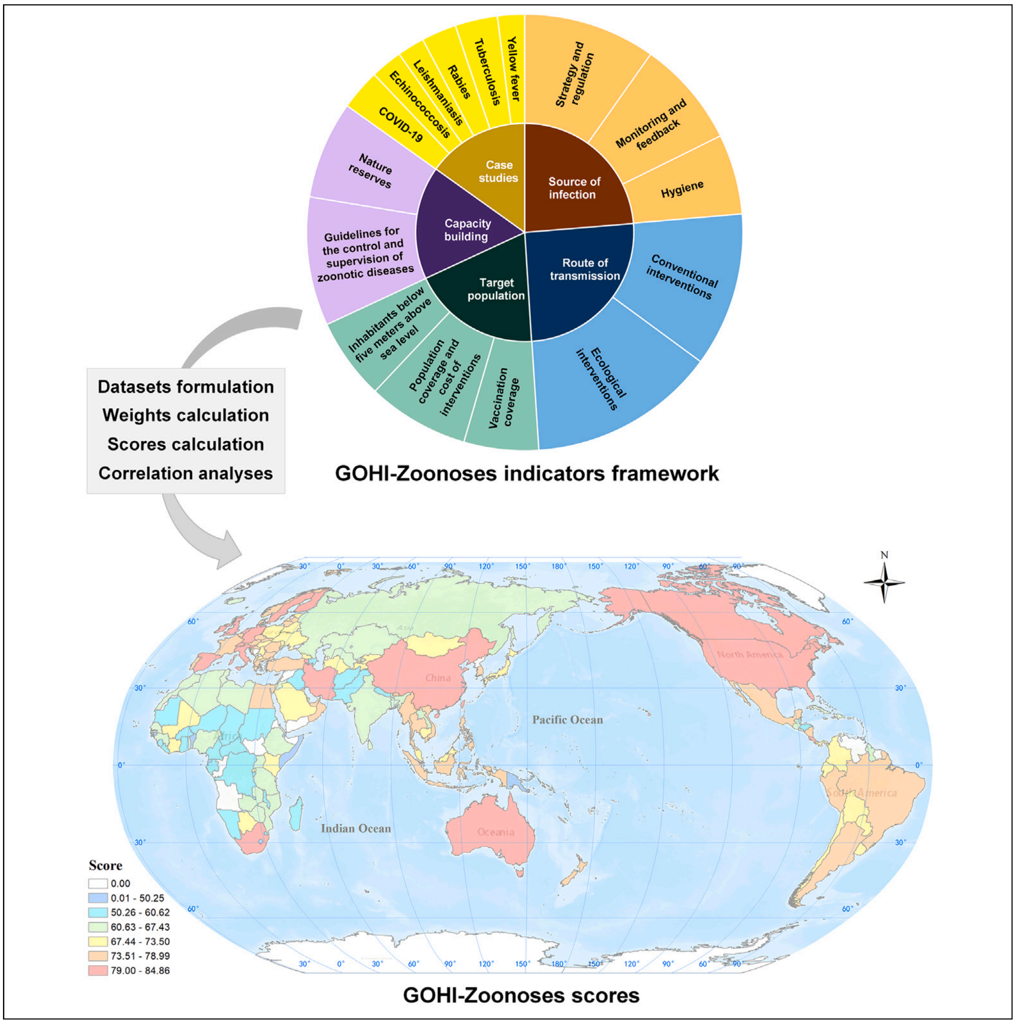
iScience

CellPress
OPEN ACCESS

Article

Global One Health index for zoonoses: A performance assessment in 160 countries and territories



Zhi-Shan Sun, Er-Ya Wan, Yannick Luther Agbana, ..., Yi Zhang, Xiao-Nong Zhou, Kokouvi Kassegne

chenjh@nipd.chinacdc.cn
(J.-H.C.)
zhangyi@nipd.chinacdc.cn (Y.Z.)
xiao-nong.zhou@sjtu.edu.cn
(X.-N.Z.)
kassegnek@sjtu.edu.cn (K.K.)

Highlights

GOHI-Zoonoses evaluates the One Health performance of zoonosis prevention and control

GOHI-Zoonoses scores vary significantly across countries and regions

Several factors associated with GOHI-Zoonoses scores were found

The Human Development Index is a significant contributor to the GOHI-Zoonoses score

Sun et al., iScience ■ ■, 109297
■ ■, 2024 © 2024 The Authors.
https://doi.org/10.1016/j.isci.2024.109297

Please cite this article in press as: Sun et al., Global One Health index for zoonoses: A performance assessment in 160 countries and territories, iScience (2024), https://doi.org/10.1016/j.isci.2024.109297

iScience

CellPress
OPEN ACCESS

Article

Global One Health index for zoonoses: A performance assessment in 160 countries and territories

Zhi-Shan Sun,[1,2] Er-Ya Wan,[1,2] Yannick Luther Agbana,[3] Han-Qing Zhao,[1,2] Jing-Xian Yin,[1,2] Tian-Ge Jiang,[1,2] Qin Li,[4] Si-Wei Fei,[1,2] Logan Blair Wu,[1,2,5,6] Xin-Chen Li,[1,2] Qi-Yu Zhang,[1,2] Jing-Shu Liu,[1,2] Si-Yu Gu,[1,2] Zhao-Yu Guo,[4] Jing-Bo Xue,[4] Le-Fei Han,[1,2] Xiao-Xi Zhang,[1,2] Shang Xia,[4] Susan Christina Welburn,[7,8] Moses Okpeku,[9] Xiao-Kui Guo,[1,2] Zhao-Jun Wang,[1,2] Jun-Hu Chen,[4,*] Yi Zhang,[4,*] Xiao-Nong Zhou,[1,2,*] and Kokouvi Kassegne[1,2,10,*]

SUMMARY

The One Health (OH) approach is used to control/prevent zoonotic events. However, there is a lack of tools for systematically assessing OH practices. Here, we applied the Global OH Index (GOHI) to evaluate the global OH performance for zoonoses (GOHI-Zoonoses). The fuzzy analytic hierarchy process algorithm and fuzzy comparison matrix were used to calculate the weights and scores of five key indicators, 16 sub-indicators, and 31 datasets for 160 countries and territories worldwide. The distribution of GOHI-Zoonoses scores varies significantly across countries and regions, reflecting the strengths and weaknesses in controlling or responding to zoonotic threats. Correlation analyses revealed that the GOHI-Zoonoses score was associated with economic, sociodemographic, environmental, climatic, and zoological factors. Additionally, the Human Development Index had a positive effect on the score. This study provides an evidence-based reference and guidance for global, regional, and country-level efforts to optimize the health of people, animals, and the environment.

INTRODUCTION

Zoonoses are infectious diseases that are transmitted from animals to humans.[1] They are caused by bacteria, viruses, fungi, parasites, and prions[2] through direct or indirect contact, vector-borne transmission, or contaminated food.[3] More than 60% of known infectious diseases are zoonotic in origin, and approximately 75% of new diseases originate from wild or domestic animals.[4,5] Zoonotic diseases affect more than two billion people globally each year, causing approximately two million deaths and billions of USD in economic losses.[6] In the last ten years, the world has faced several international public health emergencies of zoonotic origin, including the Middle East respiratory syndrome (MERS), Ebola, and coronavirus disease 2019 (COVID-19) pandemics.[7,8]

A global strategy involving meaningful cooperation based on the efficient integration of surveillance at all levels, including interdisciplinary and interdepartmental integration for effective management, is urgently needed to prevent future zoonotic pandemics. The present challenge is to move the development of a One Health (OH) paradigm from an individual- or disease-centered approach to a system-wide or community-based approach. OH is an integrated, unifying approach to balance and optimize the health of people, animals, and ecosystems,[9–11] and an effective OH framework will be crucial for mitigating zoonotic threats. The One Health High-Level Expert Panel (OHHLEP)[12] was established to promote sustainable OH development to prevent, predict, detect, and respond to global health threats.[13] However, tools for the systematic assessment of OH implementation success are lacking.

---

[1] School of Global Health, Chinese Centre for Tropical Diseases Research, Shanghai Jiao Tong University School of Medicine, Shanghai 200025, China
[2] One Health Center, Shanghai Jiao Tong University-The University of Edinburgh, Shanghai 200025, China
[3] Pan African University Life and Earth Sciences Institute (PAULESI), University of Ibadan, Ibadan, Nigeria
[4] National Health Commission of the People's Republic of China (NHC) Key Laboratory of Parasite and Vector Biology, National Institute of Parasitic Diseases at Chinese Centre for Disease Control and Prevention, Chinese Centre for Tropical Diseases Research, WHO Collaborating Centre for Tropical Diseases, National Centre for International Research on Tropical Diseases of the Chinese Ministry of Science and Technology, Shanghai 200025, China
[5] Population Health and Immunity Division, Walter and Eliza Hall Institute of Medical Research, Parkville, Melbourne, VIC 3052, Australia
[6] Department of Medical Biology, University of Melbourne, Grattan Street, Parkville, Melbourne, VIC 3010, Australia
[7] Infection Medicine, Deanery of Biomedical Sciences, College of Medicine and Veterinary Medicine, The University of Edinburgh, Edinburgh EH8 9JZ, Scotland, UK
[8] Zhejiang University – University of Edinburgh Institute, Zhejiang University, International Campus, Haining, Zhejiang 314400, China
[9] Discipline of Genetics, School of Life Sciences, University of KwaZulu-Natal, Durban, South Africa
[10] Lead contact
*Correspondence: chenjh@nipd.chinacdc.cn (J.-H.C.), zhangyi@nipd.chinacdc.cn (Y.Z.), xiao-nong.zhou@sjtu.edu.cn (X.-N.Z.), kassegnek@sjtu.edu.cn (K.K.)
https://doi.org/10.1016/j.isci.2024.109297

© 2024 The Authors.
This is an open access article under the CC BY-NC license (http://creativecommons.org/licenses/by-nc/4.0/).

Please cite this article in press as: Sun et al., Global One Health index for zoonoses: A performance assessment in 160 countries and territories, iScience (2024), https://doi.org/10.1016/j.isci.2024.109297

The United States of America's Centers for Disease Control and Prevention (USA CDC) developed the One Health Zoonotic Disease Prioritization (OHZDP) tool in 2013. According to the OH concept, the tool uses the three dimensions of people, animals, and the environment to rank zoonotic diseases in a country, optimize the allocation of prevention and control resources, strengthen monitoring, and identify future recommendations and action plans.[14,15] Another approach involves the Generalizable One Health Framework (GOHF), which describes how jurisdictions can use an OH approach to improve multisectoral collaboration and enhance the prevention and control of zoonotic diseases.[10] However, the capacity to control zoonotic threats from a global perspective and gaps in zoonotic disease governance are still unknown.

Recently, our group developed an evaluation system for global OH performance: the Global OH Index (GOHI). It is an OH-based framework for assessing international zoonotic disease control capacity.[16,17] Here, we applied the GOHI to evaluate the global OH performance for zoonoses (GOHI-Zoonoses), including the capacity for zoonosis control and the ability of countries to prevent, detect, and respond to zoonotic threats/events. The results of applying the GOHI to zoonoses provide guidance for optimizing the health of people, animals, and the environment.

RESULTS

The framework and datasets of GOHI-Zoonoses

The framework of the GOHI-Zoonoses consists of five key indicators, 16 subindicators, and 31 datasets (Figure 1A; Table 1). The five key indicators were as follows.

1. Source of infection (SI) with three subindicators: strategy and regulation [SR], monitoring and feedback [MF], and hygiene [HYG]. The dataset selected for this indicator focused on the detection, monitoring, and assessment of risk factors for human, livestock, and wildlife health; vectors; the natural environment; and the coverage and accessibility of basic sanitation facilities and health services.
2. Route of transmission (RT) with two subindicators: conventional interventions [CI] and ecological interventions [ECI]. Its datasets focused on testing and preventing pathogen, host, and vector infections.
3. Target population (TP) with three subindicators: vaccination coverage [VAC], population coverage and cost of interventions [PIC], and inhabitants below five meters above sea level [IHB]. Its datasets focused on population vaccine coverage and cost.
4. Capacity building (CB) with two subindicators: guidelines for the control and supervision of zoonotic diseases [GCS] and nature reserves [NR]. Its datasets are related to the evaluation of national guidelines, laws, and regulations related to zoonotic diseases and vaccines, as well as the control of neglected tropical diseases and vector-borne diseases.
5. Case studies (CS) with six subindicators: well-known zoonotic diseases of serious health threats—echinococcosis, leishmaniasis, tuberculosis, yellow fever, rabies, and COVID-19—were included as CS. Its datasets included disability-adjusted life years (DALYS) and/or infection number, death, and vaccination coverage.

Among the five key indicators, RT had the highest (25.31%) weight, followed by SI (23.70%), TP (19.09%), and CB (16.77%) (Table S1).

Geographical distribution of GOHI-Zoonoses scores

One hundred and sixty countries and territories worldwide were included in this study; 21 were in East Asia and the Pacific, 47 were in Europe and Central Asia, 23 were in Latin America and the Caribbean, 18 were in the Middle East and North Africa, two were in North America, eight were in South Asia, and 41 were in sub-Saharan Africa. The global median GOHI-Zoonoses score was 58.76 (interquartile range [IQR]: 55.96–63.92). The median GOHI-Zoonoses scores in East Asia and Pacific, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa, North America, South Asia, and sub-Saharan Africa were 73.25 (IQR: 63.87–78.18), 75.49 (IQR: 70.43–78.80), 69.22 (IQR: 64.52–73.39), 68.71 (IQR: 64.78–73.94), 82.76 (IQR: 82.51–83.02), 60.93 (IQR: 59.53–66.55), and 58.76 (IQR: 55.96–63.92), respectively (Figure 1B). Notably, the North American region had the highest median score, while sub-Saharan Africa had the lowest median score.

Higher scores were found in North American, European, and East Asian territories and in Australia (Figure 1C; Tables S2 and S3). According to the global ranking of GOHI-Zoonoses by country (Table S2), Germany received the highest score (84.86) and the Solomon Islands received the lowest score (43.01).

Scores of GOHI-Zoonoses for the selected indicators

The average score on the GOHI-Zoonoses scale was 68.06. The average scores for the SI, RT, TP, CB, and CS key indicators were 69.22, 59.30, 59.90, 72.85, and 85.89, respectively. For the key indicator SI, the scores of most countries were distributed in the range of 50–80, while few countries scored above 90 points, with obvious variability. The scores of most countries fell in the range of 40–80 in RT, while they ranged from 40 to 50 and 70 to 80 in TP. Most of the CB scores were concentrated between 70 and 80. The CS scores were high overall, with most of them being distributed in the 80–90 range (Figure 2A).

The highest average score of the subindicator was attributed to monitoring and feedback in the SI (83.56), ecological interventions in the RT (69.84), inhabitants below five meters above sea level in the TP (86.77), nature reserves in the CB (95.36), and tuberculosis in the CS (98.18) (Figure 2B).

Country economic status and performance in GOHI-Zoonoses

A wide gap in GOHI-Zoonoses scores was observed between regions. Among the key SI indicators, North American countries had the highest score (median: 96.86, IQR: 96.81–96.90) for the SI key indicator, followed by European and Central Asian countries (median: 82.81,

Please cite this article in press as: Sun et al., Global One Health index for zoonoses: A performance assessment in 160 countries and territories, iScience (2024), https://doi.org/10.1016/j.isci.2024.109297

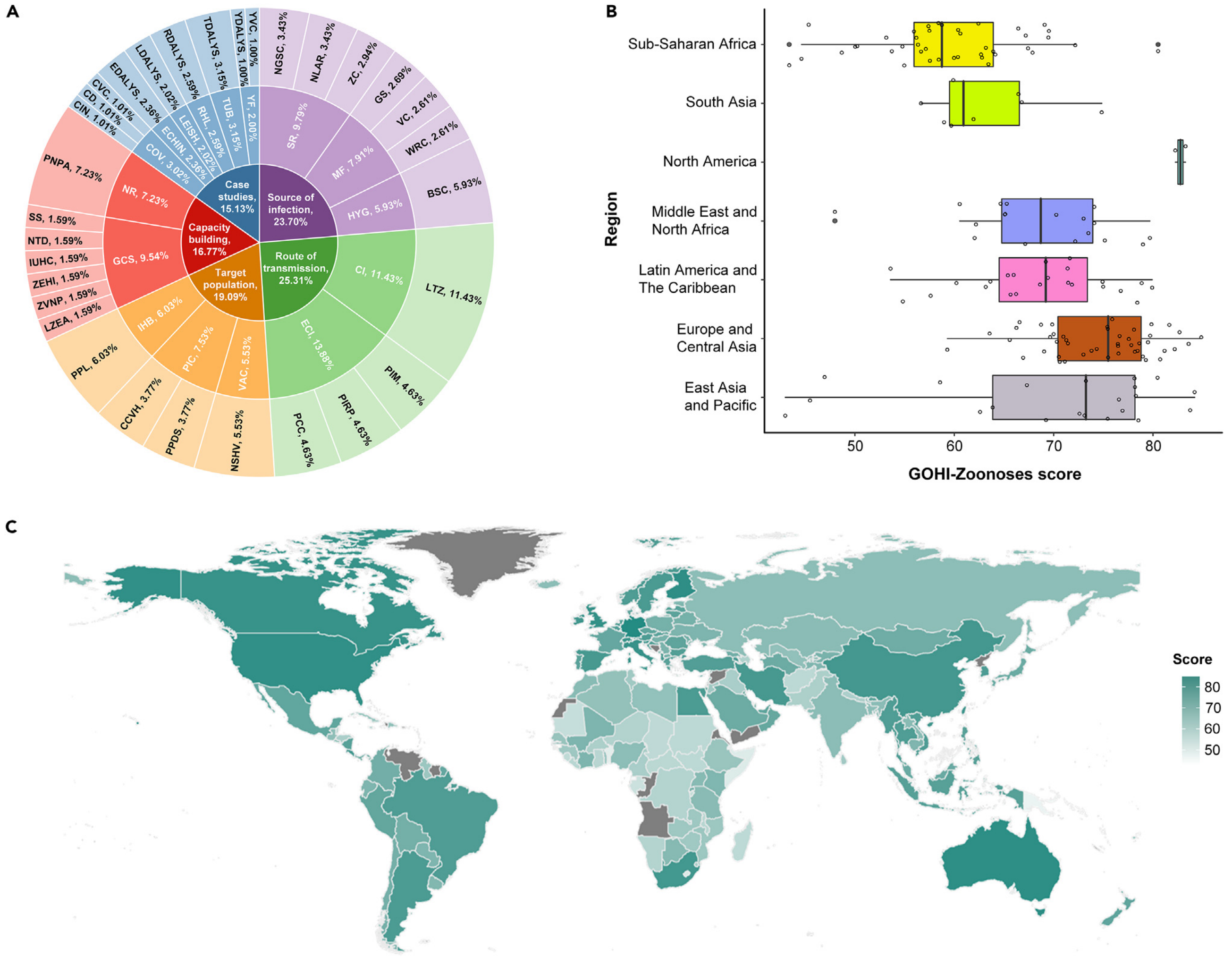


Figure 1. The indicator framework and geographical distribution of the GOHI-Zoonoses scores

(A) The indicator framework of GOHI-Zoonoses and weighted values. The innermost layer: key indicators; the middle layer: subindicators; and the outermost layer: datasets. SR: Strategy and regulation, MF: Monitoring and feedback, HYG: Hygiene, CI: Conventional intervention, ECI: Ecological interventions, VAC: Vaccination coverage, PIC: Population coverage and cost of interventions, IHB: Inhabitants below five meters above sea level, GCS: Guidelines for the control and supervision of zoonotic diseases, NR: Nature reserves, COV: COVID-19, ECHIN: Echinococcosis, LEISH: Leishmaniasis, RHL: Rabies, TUB: Tuberculosis, YF: Yellow fever. NGSC: National guideline for surveillance/control, NLAR: National legislation on animal reservoirs, ZC: Zoonosis capacity score, GS: General surveillance, VC: Vector control, WRC: Wildlife reservoirs control, BSC: Basic sanitation services, LTZ: Laboratory testing for zoonotic reservoirs, PIM: Policy adoption of insecticide-treated mosquito nets, PIRP: Policy adoption of indoor residual spraying, PCC: Prevention chemotherapy coverage of zoonoses, NSHV: National strategy and regulation for human/animal vaccination, PPDS: Proportion of population having basic drinking water and sanitation facilities, CCVH: Costs directed to chemotherapy/vaccination of humans, PPL: Proportion of population living in areas where the elevation is less than 5 m, LZEA: Legislation of zoonosis educational activities, ZVNP: Zoonosis vaccine national plan, ZEHI: Zoonotic events and the human-animal Interface, IUHC: Universal health coverage (UHC) service subindex on infectious diseases, NTD: Neglected tropical disease control and prevention, SS: Surveillance, PNPA: Proportion of natural protected areas, CIN: COVID-19 infection number, CD: COVID-19 deaths, CVC: COVID-19 Vaccination coverage, EDALYS: Echinococcosis human DALYS, LDALYS: Leishmaniasis human DALYS, RDALYS: Rabies human DALYS, TDALYS: Tuberculosis Human DALYS, YDALYS: Yellow fever DALYS, YVC: Yellow fever vaccination.

(B) The scores of GOHI-Zoonoses per region. The boxplot colors represent different regions. The dots represent the 160 countries and territories involved in this study.

(C) Global score map of GOHI-Zoonoses. The different colors represent different score ranges for GOHI-Zoonoses. Gray represents missing data.

IQR: 76.71–86.44), while the lowest scores were observed in sub-Saharan Africa (median: 50.96, IQR: 45.86–61.58) and South Asia (median: 59.44, IQR: 55.69–66.57). For the RT key indicator, Latin America and the Caribbean, the Middle East and North Africa, and sub-Saharan Africa had lower average scores (median: 55.83, IQR: 42.86–66.64; median: 56.24, IQR: 45.22–60.91; median: 52.50, IQR: 44.84–64.90, respectively). In addition, South Asia and sub-Saharan Africa had relatively lower scores for TP (median: 47.76, IQR: 53.21–53.91 and median: 45.47, IQR: 37.74–60.62, respectively) and CB (median: 73.59, IQR: 68.60–77.04 and median: 72.01, IQR: 69.06–73.81, respectively) (Figure 2C).

Please cite this article in press as: Sun et al., Global One Health index for zoonoses: A performance assessment in 160 countries and territories, iScience (2024), https://doi.org/10.1016/j.isci.2024.109297

Table 1. Data sources for GOHI-Zoonoses

Dataset	Missing data (%)	Data source
National guideline for surveillance/control	11.40	GHS index (https://ghsindex.org/)
National legislation on animal reservoirs	11.40	
Laboratory testing for zoonotic reservoirs	26.40	
National strategy and regulation for human/animal vaccination	14.10	
Zoonotic capacity score	13.20	WHO (https://who.int/)
Policy adoption of insecticide-treated mosquito nets	13.20	
Policy adoption of indoor residual spraying	18.20	
Prevention chemotherapy coverage of zoonoses	13.60	
Costs directed to chemotherapy/vaccination of humans	63.60	
Legislation of educational activities on zoonoses	63.60	
National program of vaccines against zoonotic diseases	55.50	
Zoonotic events and the human-animal interface	11.80	
Universal health coverage service subindex on infectious diseases	13.20	
Neglected tropical diseases control and prevention	83.60	
Surveillance	5.50	
COVID-19 infection number	29.50	
COVID-19 deaths	19.50	
COVID-19 vaccination coverage	29.50	
Yellow fever vaccination	20.00	
General surveillance	20.00	WOAH (https://woah.org/)
Vector control	32.30	
Wildlife reservoirs control	20.00	
Basic sanitation services	1.80	World Bank (https://worldbank.org/en/home)
Proportion of population having basic drinking water and sanitation facilities	1.80	
Proportion of population living in the areas where elevation is below five meters	2.70	
Proportion of natural protected areas	10.50	
Echinococcosis human DALYS	10.50	GHDx (https://ghdx.healthdata.org/)
Leishmaniasis human DALYS	10.50	
Rabies human DALYS	10.50	
Tuberculosis human DALYS	10.50	
Yellow fever DALYS	6.40	

The proportion of missing data refers to the ratio of the number of countries/territories missing a certain dataset to the total number of countries/areas.

We observed disparities between low-income countries (LICs) and the global average for hygiene (gap = −49.01), conventional intervention (gap = −16.93), vaccine regulation (gap = −20.24), and health facility population coverage and costs of interventions (gap = −26.81). However, high-income countries (HICs) scored higher than the global average for strategy and regulation of SI (gap = 15.85), hygiene (gap = 19.76), and conventional intervention (gap = 14.06). The sub-Saharan African region exhibited large disparities compared to the global average for strategy and regulation adoption for zoonotic sources (gap = −14.75), hygiene (gap = −37.53), and conventional interventions (gap = −16.61). In South Asia, substantial deficits were found between countries and the global average for strategy and regulation adoption for zoonotic sources (gap = −15.53), vaccine regulation (gap = −27.78), echinococcosis (gap = −15.56), leishmaniasis (gap = −18.80), rabies (gap = −15.42), and tuberculosis (gap = −14.25). Latin America and the Caribbean region exhibited poor vaccine regulation (gap = −13.24). The East Asia and Pacific region had relatively low scores for monitoring and feedback from infectious sources (gap = −11.91). The scores for Europe and Central Asia for COVID-19 prevention and control were below the global average (gap = −11.84). Most North American countries had scores above the global average for most indicators (Figure 3; Table S4).

GOHI-Zoonoses is positively correlated with economic, sociodemographic, environmental, climatic, and zoological factors

The GOHI-Zoonoses score exhibited strong positive correlations with gross domestic product (GDP) per capita ($r_s = 0.62$, $p < 0.0001$), gross national income (GNI) per capita ($r_s = 0.62$, $p < 0.0001$), life expectancy ($r_s = 0.64$, $p < 0.0001$), and human development index (HDI) ($r_s = 0.68$,

Please cite this article in press as: Sun et al., Global One Health index for zoonoses: A performance assessment in 160 countries and territories, iScience (2024), https://doi.org/10.1016/j.isci.2024.109297

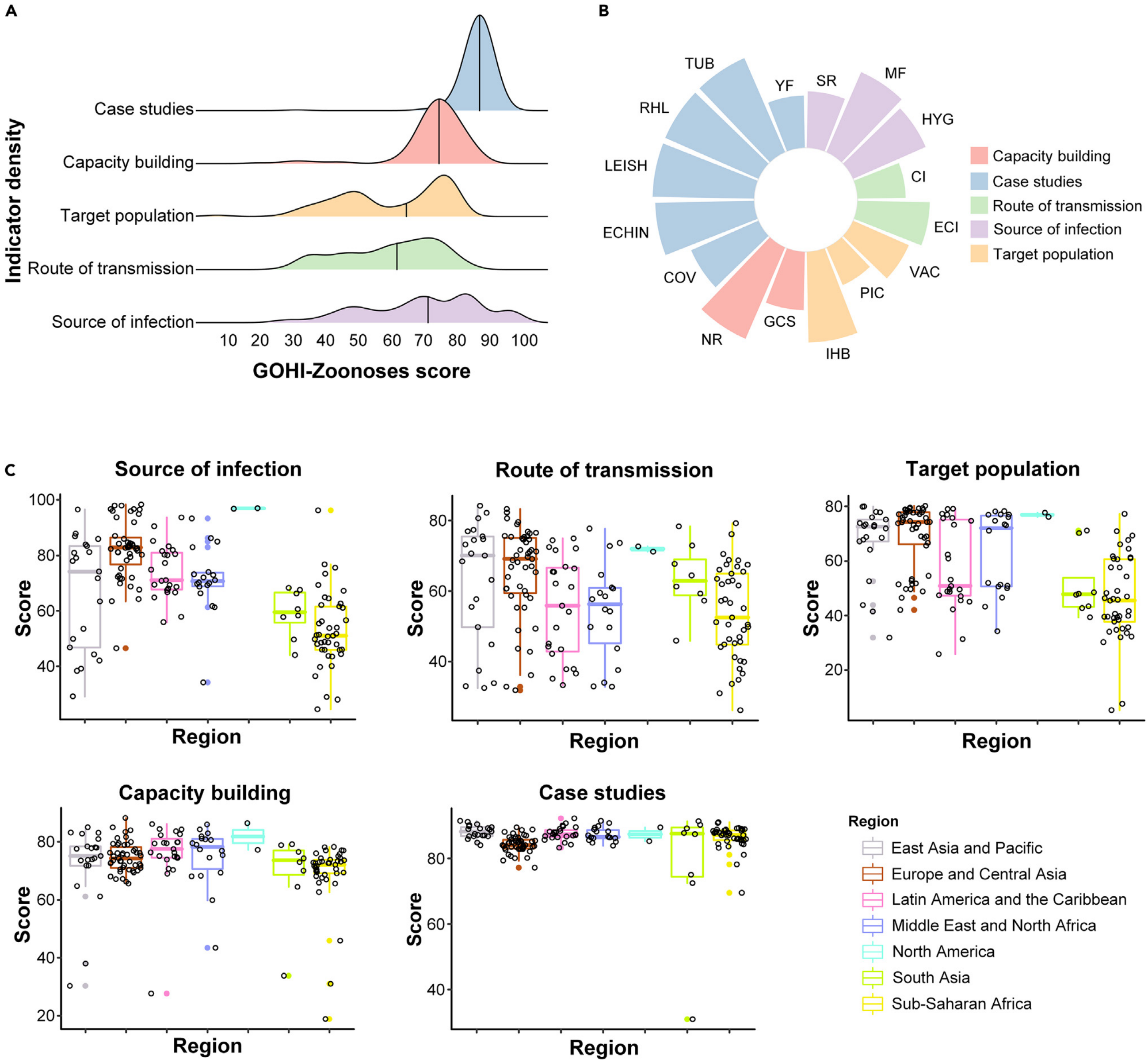


Figure 2. The global scores of GOHI-Zoonoses

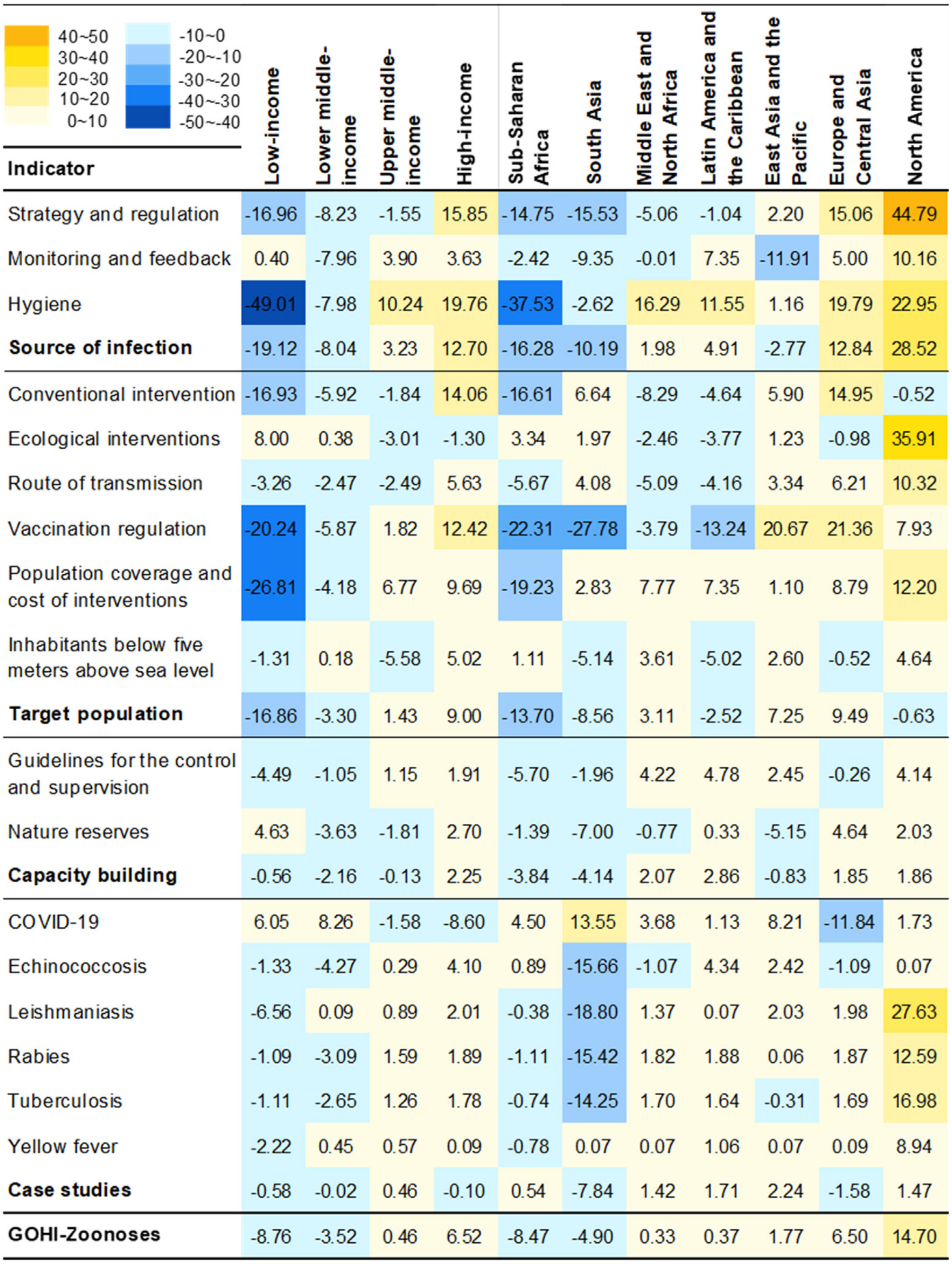
(A) The scores of GOHI-Zoonoses in relation to key indicators.

(B) The scores of GOHI-Zoonoses in relation to subindicators. SR: strategy and regulation; MF: monitoring and feedback; HYG: hygiene; CI: conventional intervention; ECI: ecological intervention; VAC: vaccination coverage; PIC: population coverage and cost of intervention; IHB: inhabitants below five meters above sea level; GCS: guidelines for the control and supervision of zoonotic diseases; NR: nature reserves; COV: COVID-19; ECHIN: echinococcosis; LEISH: leishmaniasis; RHL: rabies; TUB: tuberculosis; YF: yellow fever. The length of each rose petal represents the mean of the sub-I indicators.

(C) The scores of GOHI-Zoonoses in relation to key indicators by region. C1: The score of each region according to the source of infection. C2: The score of each region according to the route of transmission. C3: The score of each region according to the target population. C4: The score of each region according to capacity building. C5: The score of each region according to the case studies. The different boxplot colors represent different regions. The dots represent the 160 countries and territories involved in this study.

$p < 0.0001$). Additionally, the GOHI-Zoonoses score showed a moderate positive correlation with the environmental performance index (EPI) ($r_s = 0.41$, $p < 0.0001$). Livestock density[18] ($r_s = 0.2$, $p < 0.05$) and tree cover loss ($r_s = 0.28$, $p < 0.05$) were weakly positively correlated with GOHI-Zoonoses scores. From the scatterplot, we found that approximately 70% of the countries are concentrated in areas with livestock density ≤ 1 and scores ≥ 58.76 (the global median GOHI-Zoonoses score). That is, countries with low livestock densities have GOHI-Zoonoses scores above the median. Spearman's correlation between GOHI-Zoonoses and external factors revealed that the GDP, GNI, life expectancy,

Please cite this article in press as: Sun et al., Global One Health index for zoonoses: A performance assessment in 160 countries and territories, iScience (2024), https://doi.org/10.1016/j.isci.2024.109297



Indicator	Low-income	Lower middle-income	Upper middle-income	High-income	Sub-Saharan Africa	South Asia	Middle East and North Africa	Latin America and the Caribbean	East Asia and the Pacific	Europe and Central Asia	North America
Strategy and regulation	-16.96	-8.23	-1.55	15.85	-14.75	-15.53	-5.06	-1.04	2.20	15.06	44.79
Monitoring and feedback	0.40	-7.96	3.90	3.63	-2.42	-9.35	-0.01	7.35	-11.91	5.00	10.16
Hygiene	-49.01	-7.98	10.24	19.76	-37.53	-2.62	16.29	11.55	1.16	19.79	22.95
Source of infection	-19.12	-8.04	3.23	12.70	-16.28	-10.19	1.98	4.91	-2.77	12.84	28.52
Conventional intervention	-16.93	-5.92	-1.84	14.06	-16.61	6.64	-8.29	-4.64	5.90	14.95	-0.52
Ecological interventions	8.00	0.38	-3.01	-1.30	3.34	1.97	-2.46	-3.77	1.23	-0.98	35.91
Route of transmission	-3.26	-2.47	-2.49	5.63	-5.67	4.08	-5.09	-4.16	3.34	6.21	10.32
Vaccination regulation	-20.24	-5.87	1.82	12.42	-22.31	-27.78	-3.79	-13.24	20.67	21.36	7.93
Population coverage and cost of interventions	-26.81	-4.18	6.77	9.69	-19.23	2.83	7.77	7.35	1.10	8.79	12.20
Inhabitants below five meters above sea level	-1.31	0.18	-5.58	5.02	1.11	-5.14	3.61	-5.02	2.60	-0.52	4.64
Target population	-16.86	-3.30	1.43	9.00	-13.70	-8.56	3.11	-2.52	7.25	9.49	-0.63
Guidelines for the control and supervision	-4.49	-1.05	1.15	1.91	-5.70	-1.96	4.22	4.78	2.45	-0.26	4.14
Nature reserves	4.63	-3.63	-1.81	2.70	-1.39	-7.00	-0.77	0.33	-5.15	4.64	2.03
Capacity building	-0.56	-2.16	-0.13	2.25	-3.84	-4.14	2.07	2.86	-0.83	1.85	1.86
COVID-19	6.05	8.26	-1.58	-8.60	4.50	13.55	3.68	1.13	8.21	-11.84	1.73
Echinococcosis	-1.33	-4.27	0.29	4.10	0.89	-15.66	-1.07	4.34	2.42	-1.09	0.07
Leishmaniasis	-6.56	0.09	0.89	2.01	-0.38	-18.80	1.37	0.07	2.03	1.98	27.63
Rabies	-1.09	-3.09	1.59	1.89	-1.11	-15.42	1.82	1.88	0.06	1.87	12.59
Tuberculosis	-1.11	-2.65	1.26	1.78	-0.74	-14.25	1.70	1.64	-0.31	1.69	16.98
Yellow fever	-2.22	0.45	0.57	0.09	-0.78	0.07	0.07	1.06	0.07	0.09	8.94
Case studies	-0.58	-0.02	0.46	-0.10	0.54	-7.84	1.42	1.71	2.24	-1.58	1.47
GOHI-Zoonoses	-8.76	-3.52	0.46	6.52	-8.47	-4.90	0.33	0.37	1.77	6.50	14.70

Figure 3. Economic status and regional performance for GOHI-Zoonoses

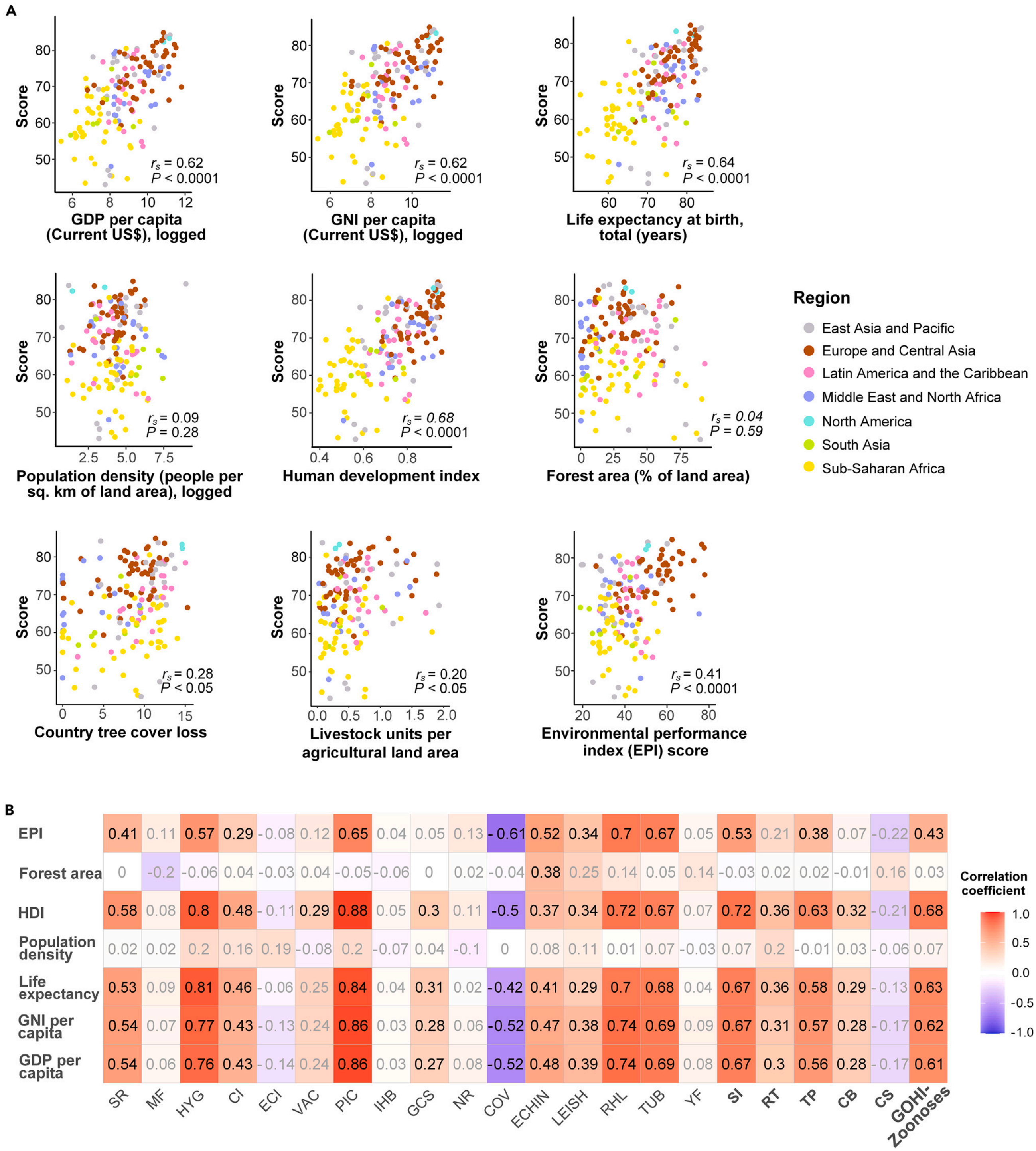
The numbers represent the difference between the indicator scores and the global average and are shown in shades of color.

and HDI were strongly positively correlated with hygiene, population coverage and the cost of interventions, rabies, and tuberculosis sub-indicators (Figure 4).

Multiple linear regression analysis revealed that HDI positively affected GOHI-Zoonoses scores

The multiple linear regression model was found to be statistically significant (F value = 19.14, $p < 0.01$). The residuals of the multiple linear regression model were normally distributed and independent and had equal variance ($p = 0.4180$, Durbin-Watson test statistic = 1.95; Figure S1). However, multicollinearity existed (variance inflation factor [VIF] >10). The best-fit model was estimated to be least absolute shrinkage and selection operator (LASSO), with a lambda of 1.14 (Figure S2), which minimized the mean squared error (MSE). The HDI was selected

Please cite this article in press as: Sun et al., Global One Health index for zoonoses: A performance assessment in 160 countries and territories, iScience (2024), https://doi.org/10.1016/j.isci.2024.109297



	SR	MF	HYG	CI	ECI	VAC	PIC	IHB	GCS	NR	COV	ECHIN	LEISH	RHL	TUB	YF	SI	RT	TP	CB	CS	GOHI-Zoonoses
EPI	0.41	0.11	0.57	0.29	-0.08	0.12	0.65	0.04	0.05	0.13	-0.61	0.52	0.34	0.7	0.67	0.05	0.53	0.21	0.38	0.07	-0.22	0.43
Forest area	0	-0.2	-0.06	0.04	-0.03	0.04	-0.05	-0.06	0	0.02	-0.04	0.38	0.25	0.14	0.05	0.14	-0.03	0.02	0.02	-0.01	0.16	0.03
HDI	0.58	0.08	0.8	0.48	-0.11	0.29	0.88	0.05	0.3	0.11	-0.5	0.37	0.34	0.72	0.67	0.07	0.72	0.36	0.63	0.32	-0.21	0.68
Population density	0.02	0.02	0.2	0.16	0.19	-0.08	0.2	-0.07	0.04	-0.1	0	0.08	0.11	0.01	0.07	-0.03	0.07	0.2	-0.01	0.03	-0.06	0.07
Life expectancy	0.53	0.09	0.81	0.46	-0.06	0.25	0.84	0.04	0.31	0.02	-0.42	0.41	0.29	0.7	0.68	0.04	0.67	0.36	0.58	0.29	-0.13	0.63
GNI per capita	0.54	0.07	0.77	0.43	-0.13	0.24	0.86	0.03	0.28	0.06	-0.52	0.47	0.38	0.74	0.69	0.09	0.67	0.31	0.57	0.28	-0.17	0.62
GDP per capita	0.54	0.06	0.76	0.43	-0.14	0.24	0.86	0.03	0.27	0.08	-0.52	0.48	0.39	0.74	0.69	0.08	0.67	0.3	0.56	0.28	-0.17	0.61

Figure 4. Scatterplots and correlations (Spearman's r) between external variables and the GOHI-Zoonoses score

(A) Scatterplots between external variables and the GOHI-Zoonoses score. A1: GDP per capita (current US$). A2: GNI per capita (current US$). A3: Life expectancy at birth, total (years). A4: Population density (people per sq. km of land area), Logged. E: Human Development Index. A5: Forest area (% of land area). A6: Environmental Performance index. For A1-A6, the regions were distinguished by seven colored dots, which represent the 160 countries and territories involved in this study.

(B) Spearman correlation between the indicators and external economic, sociodemographic, environmental, and climatic factors. The SI, RT, TP, CB, and CS are the key indicators. SR, MF, HYG, CI, ECI, VAC, PIC, IHB, GCS, NR, COV, ECHIN, LEISH, RHL, TUB, and YF are the subindicators. A p value greater than or equal to 0.05 is indicated in gray. r_s: Spearman's rank correlation coefficient. GDP: Gross domestic product. GNI: Gross national income. EPI: Environmental performance

Please cite this article in press as: Sun et al., Global One Health index for zoonoses: A performance assessment in 160 countries and territories, iScience (2024), https://doi.org/10.1016/j.isci.2024.109297

Figure 4. *Continued*

index. SI: source of infection; RT: route of transmission; TP: target population; CB: capacity building; CS: case studies; SR: strategy and regulation; MF: monitoring and feedback; HYG: hygiene; CI: conventional interventions; ECI: ecological interventions; VAC: vaccination coverage; PIC: population coverage and cost of interventions; IHB: inhabitants below five meters above sea level; GCS: guidelines for the control and supervision of zoonotic diseases; NR: nature reserves; COV: COVID-19; ECHIN: echinococcosis; LEISH: leishmaniasis; RHL: rabies; TUB: tuberculosis; YF: yellow fever. The shades of color and the numbers in the square boxes represent the magnitude of Spearman's correlation coefficient (r_s).

through LASSO regression. According to the linear regression model constructed with the GOHI-Zoonoses and HDI data, the regression coefficient was 36.7 ($p < 0.001$), and the F value of the linear regression model was 68.64 ($p < 0.05$). The residuals of the linear regression model were normally distributed, independent, and equal in variance ($p = 0.2630$, Durbin-Watson test statistic = 1.85; Figure S3).

HICs have higher GOHI-Zoonoses scores than LICs

The Shapiro-Wilk test showed that the data for GOHI-Zoonoses and key indicators were nonnormally distributed ($p < 0.001$). The Kruskal-Wallis test demonstrated differences in GOHI-Zoonoses scores among countries with different economic levels. The GOHI-Zoonoses score for HICs (median: 75.45, IQR: 71.44–79.50) was significantly greater than that for upper-middle-income countries (UMICs) (median: 69.33, IQR: 63.58–74.98, $p = 0.008$), lower-middle-income countries (LMICs) (median: 66.45, IQR: 60.22–70.27, $p < 0.0001$), and LICs (median: 57.97, IQR: 56.44–63.09, $p < 0.0001$). The GOHI-Zoonoses score for UMICs was significantly greater than that for LICs ($p = 0.001$). Moreover, HICs exhibited significantly greater scores (median: 83.90, IQR: 73.04–92.79) for sources of infection for zoonotic diseases than did UMICs (median: 72.13, IQR: 67.56–82.43, $p = 0.017$), LMICs (median: 63.38, IQR: 49.64–71.66, $p < 0.0001$), and LICs (median: 49.12, IQR: 44.71–55.04, $p < 0.0001$). UMICs received higher scores than LMICs ($p = 0.013$) and LICs ($p < 0.0001$) for the SI. HICs (median: 68.14, IQR: 57.84–74.85) exhibited significantly greater scores for transmission than did LMICs (median: 60.60, IQR: 43.69–70.01). Nevertheless, no significant difference was observed between the HIC and LIC scores in terms of the RT ($p = 0.062$). With respect to protection of the target population, HICs (median: 75.13, IQR: 56.99–78.08) had higher scores than did UMICs (median: 66.11, IQR: 48.81–75.76, $p = 0.04$), LMICs (median: 54.24, IQR: 43.37–71.90, $p < 0.0001$), and LICs (median: 39.30, IQR: 34.84–59.88, $p < 0.0001$). UMICs scored higher than LICs did ($p = 0.001$). No significant differences were found between the different income levels for CB and CS (Figure 5).

DISCUSSION

By establishing an indicator framework for zoonotic diseases under the OH concept, we evaluated and ranked the occurrence and control of zoonotic threats in 160 countries/territories worldwide. We discovered disparities in GOHI-Zoonoses scores among regions and countries with different income statuses. Furthermore, the gaps between the 160 countries in each subindicator and the global average identified weaknesses in zoonotic disease prevention and control. Correlation analyses preliminarily indicated that GDP, GNI, life expectancy at birth, HDI, livestock density, tree cover loss, and EPI were associated with the GOHI-Zoonoses score. Multiple linear regression further indicated that the HDI positively affected the scores, which identified potential driving factors for differences in zoonotic disease prevention and control.

The high scores for some European and American countries might be due to early attention given to the global impact of infectious diseases, as well as the use of OH approaches to address zoonotic diseases. A standard bibliometric analysis based on OH information revealed that the USA, the UK, and Australia had the most OH-related publications, accounting for 52.9% of the total OH-related literature.[19] In 2004, the Global Disease Detection (GDD) program was created in the USA in response to the severe acute respiratory syndrome pandemic.[20] Apropos, the determination of the USA CDC is embodied in its principle of strengthening global health security by identifying, responding to, and containing emerging infectious diseases and bioterrorism threats.[21] In 2008, a strategic framework using the OH approach for reducing the risk of emerging infectious diseases at the animal-human-environment interface was established by the Food and Agriculture Organization (FAO), World Organization for Animal Health (WOAH), World Health Organization (WHO), UN System Influenza Coordination, United Nations International Children's Emergency Fund (UNICEF), and World Bank.[22] Sub-Saharan Africa has a heavy burden of zoonoses across a wide spectrum, including rabies and onchocerciasis, and now-emerging zoonoses such as anthrax, yellow fever, Ebola, Lassa fever, and COVID-19.[23] However, there was a "late" initiative in implementing the OH approach at the regional and national levels against zoonotic disease control and prevention, which was launched only in 2020.[24] The international community is increasingly recognizing the imperative nature of zoonotic disease management within the African region. For example, the involvement of the USA CDC in Kenya encompasses the delivery of OHZDP.[25]

Despite the significant variations in GOHI-Zoonoses scores across different regions, each region contains high-scoring countries. For example, South Africa was the only sub-Sahara African country with a score above 80. In recent years, South Africa has made remarkable efforts to control and prevent zoonotic events. In 2010, the South Africa GDD office became the ninth regional GDD center, and its OH program was established to detect and respond to zoonotic disease threats.[26] South Africa's experience in successfully tackling zoonotic events can serve as an example for other African jurisdictions and provide a basis for cooperation at the regional level. In Europe, Germany scored the highest for GOHI-Zoonoses, which demonstrates its ability to prevent, control, and respond to zoonotic events/threats. In 2001, the German government launched the Protection Against Infection Act, which aimed to prevent communicable diseases in humans and combat the spread of infectious diseases, including zoonoses.[27] In accordance with the Protection Against Infection Act, the European Commission issued a new directive on November 17, 2003, pertaining to the surveillance of zoonoses and zoonotic agents.[28] The spread of zoonoses has no

Please cite this article in press as: Sun et al., Global One Health index for zoonoses: A performance assessment in 160 countries and territories, iScience (2024), https://doi.org/10.1016/j.isci.2024.109297

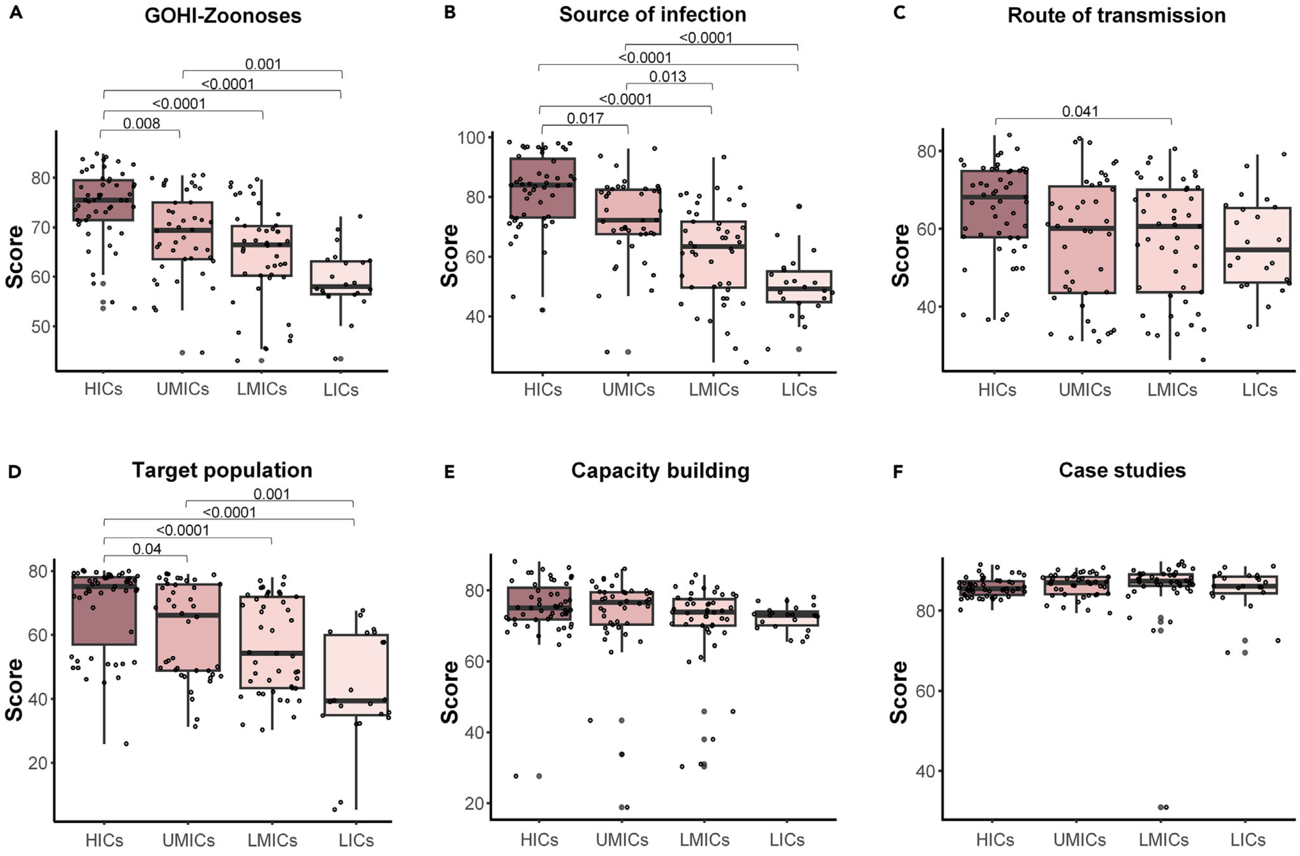


Figure 5. Scores of each indicator for countries with different economic statuses

(A) GOHI-Zoonoses scores.

(B) Scores of the source of infection indicator.

(C) Scores of the route of the transmission indicator.

(D) Scores of the target population indicators.

(E) Scores of the capacity building indicator.

(F) Scores indicating the case study. HICs: High-income countries. UMICs: Upper-middle-income countries. LMICs: Lower-middle-income countries. LICs: Low-income countries. The value on the horizontal bar represents the p value. The boxplot colors represent the different economic statuses of the countries and territories. The dots represent the 160 countries and territories involved in this study. The solid black line in the middle of the boxplot represents the median.

national boundaries, and collaboration and exchange across borders boost infectious disease transmission efficiencies. It is imperative to emphasize zoonotic disease prevention and control at national borders and strengthen regional cooperation. Regional OH initiatives and cooperation should influence the ability of a country to respond. Therefore, policies that enact global strategies for zoonoses while ensuring synergy and cohesiveness at the global and regional levels are highly valuable.

The current study indicated that HICs tend to have higher GOHI-Zoonoses scores. This could be related to stable government legislation and national strategies, effective health services, comprehensive management of zoonotic vaccines, mass vaccination, and technical excellence in zoonotic pathogen detection. Previously, HICs were found to effectively manage zoonotic diseases by investing in preventive measures.[29] Conversely, numerous LICs encounter obstacles in implementing strategies to reduce zoonotic risk due to economic factors that impact households, the business sector, and governmental entities.[30] The cost of prevention is a significant barrier for many countries, and resources for prevention are often not prioritized.[30] Low-scoring LICs are often not fully prepared for use in treating zoonotic diseases due to their fragile surveillance ability, late response system, limited medical resources, and poor awareness and education, which results in a greater risk of future zoonotic diseases.[31,32] Countries with high GOHI scores indicate strong zoonotic disease control and response capabilities; however, this does not mean that they have a low risk of zoonotic disease in the future. Zoonotic diseases can spread across borders and cause worldwide pandemics due to tourism, global migration, trade, etc. Countries need to enhance and strengthen cooperation with neighboring countries, such as through joint disease surveillance, sharing of information on animal movements, and integration and cooperation between multiple sectors[33]; additionally, the OH approach should be used to prevent, detect, predict, and respond to the threat of zoonotic diseases in border areas. This was the case in Uganda, where a multisectoral community engaged in characterizing animal mobility to prevent the cross-border spread of zoonotic diseases.[34] As a further example, in 2007, China and Myanmar established cross-border malaria prevention and control measures, which effectively reduced the burden of malaria at the China-Myanmar border.[35] Consequently, it is imperative to encourage HICs to support funding and CB in LICs to strengthen the capacity for early detection of zoonotic disease and enhance the provision of pharmaceuticals, vaccines, and related resources. For example, the United States Agency for International Development Emerging Pandemic Threats Program, which aimed to strengthen zoonotic disease surveillance and laboratory testing capacities of LMICs and LICs such as Bangladesh, Cambodia, and Vietnam,[36] will bolster the ability of these countries to prevent, detect, and respond to zoonotic threats/events (GOHI-Zoonoses scores: 66.47, 69.24, and 78.18, respectively). Despite the difficulty in quantifying the precise impacts of these investments, it remains crucial to allocate resources toward measures against the local and regional spread of zoonotic diseases.[37] OH implementation should consider social and ecological factors related to zoonotic transmission to provide comprehensive strategies for assessing and addressing zoonotic and related risks across communities, particularly those with stratified regions and customs.[38]

Zoonoses are influenced by multifaceted drivers encompassing ecological, economic, and social dynamics that operate at local to global scales.[4,39–42] Research on the drivers of zoonotic events can inform strategic decisions and optimize control strategies for zoonotic disease prevention and control. Considering the integrity of the data generated in the present study and the quality of the data, we investigated the associations of nine external-social, economic, and environmental factors with zoonotic events. Our results showed that GOHI-Zoonoses scores were greater in countries with higher GNI and GDP. Such an association aligns with the conclusion drawn earlier regarding the influence of economic status on the prevention and control of zoonotic diseases. In addition, we found that human life expectancy is positively associated with efficiency in zoonotic disease control, which is consistent with the findings of previous studies showing that higher human life expectancy is associated with fewer zoonotic parasite infections in companion animals.[43]

Previous research has indicated that deforestation leads to increased contact between humans and wild species, thereby increasing the risk of disease transmission.[44] Consequently, the preservation of forest areas and the prevention of deforestation can contribute to mitigating the risk of zoonotic diseases. The current study showed a positive correlation between tree cover loss and GOHI-Zoonoses. This study used a tree cover loss dataset that referred to trees under five meters in length or those lost from other natural factors, such as fires or storms, but not deforestation.[45] This suggests that the natural evolution of the environment rather than human-made disruption can help restore and reshape ecosystems, potentially reducing the risk of zoonotic threats. Future research may aim to differentiate between natural and anthropogenic drivers of tree cover loss to better elucidate their distinct impacts on zoonotic disease. Countries with higher human population densities may be likely to host more zoonoses than other countries.[46] In this study, more than 70% of the countries had low livestock density and high GOHI-Zoonoses scores, which is consistent with findings from other studies that high livestock density increases the risk of zoonotic diseases.[47,48] Other studies have shown that higher livestock density creates a larger potential host population with more possibilities for exposure and transmission within and between farms, which in turn can lead to greater pathogen diversification.[48] Intensive livestock farming, characterized by elevated livestock densities, is correlated with the risk of zoonotic disease emergence.[47,49] Thus, maintaining livestock density within a reasonable range is key for preventing zoonotic diseases. The EPI is a ranking system that ranks 180 countries according to climate change performance, environmental health, and ecosystem vitality.[50] We found that the EPI was positively correlated with the GOHI-Zoonoses score. In the present study, countries with low GOHI-Zoonoses and low EPI scores were mostly found in LICs, e.g., in sub-Saharan Africa. These results can be explained by these countries having incomplete policies; inadequate implementation measures for environmental and animal health, such as biodiversity conservation and animal habitats; and inappropriate exploitation of natural resources, which play roles in zoonotic threats.[23] Similarly, the East and Horn of Africa region has been identified to be at risk for the emergence and spread of zoonotic diseases because this region is threatened by rising temperatures and unpredictable rainfall. This environmental shift intensifies the proliferation and dissemination of vectorial organisms, including mosquitoes, which leads to the transmission of zoonotic infections.[51] In summary, climate change alters the living conditions of zoonotic pathogens and vectors, increasing the spread of zoonotic diseases.[52] Environmental degradation can compromise the immune system of animals, leading to the shedding of pathogens from animals into the environment, which in turn infect humans.[53] Decreased biodiversity also increases the risk of transmission of zoonotic diseases.[54] Thus, it is important to preserve the environment, reduce pollution, and protect biodiversity to prevent and control zoonotic diseases. We found no correlation between the GOHI-Zoonoses score and forest area or population density. One possible reason could be that the variables included in this study were indirect variables related to zoonosis, and the results may be influenced by other confounding factors. We also found no association between the GOHI-Zoonoses score and the incidence of zoonotic diseases, e.g., COVID-19 ($p > 0.05$), in the CS. This may be due to underreporting and limited testing capacity in LICs and LMICs,[55] which can lead to different numbers of cases or deaths than reported, such as COVID-19. To reduce reporting bias, countries need to ensure transparency in the surveillance process and document all steps taken to collect and analyze data. This includes documenting the methods used, any changes made in the process, and any limitations or biases that may exist, e.g., using standardized forms, protocols, and procedures for data collection. Quality control, which includes regular checks for errors and inconsistencies, is also needed to ensure the accuracy and reliability of the data.[56,57]

The results of multiple linear regression revealed a linear relationship between the HDI and GOHI-Zoonoses score. The HDI is a statistical composite index that measures a country's average achievements in three basic aspects of human development: a long and healthy life, knowledge, and a decent standard of living.[58] Higher HDI values indicate greater economic resources, improved education, and enhanced healthcare infrastructure, which collectively contribute better to the effective prevention and control of zoonotic disease outbreaks.[59] Regions with higher HDI values may have better access to economic resources, improved education, and enhanced healthcare infrastructure, which contributes to the development and implementation of effective governance policies for zoonotic disease prevention. These findings underscore the importance of socioeconomic development in bolstering preparedness and response mechanisms, highlighting the need for targeted interventions and policies to address zoonotic risks in less-developed areas.

Overall, the strengths of this study lie in the rigorous framework design and the selection of indicators used.[16,60] The datasets used were sourced from authoritative and public databases (Table 1). The methodology that employed algorithms has proven to be effective.[60–62] To the best of our knowledge, this study is the first global and comprehensive assessment of the performance of zoonoses based on the OH concept. The scores under each GOHI-Zoonoses indicator reflected the strengths and weaknesses in controlling or responding to zoonotic threats by country and region, which are positively associated with economic, sociodemographic, environmental, and climatic factors. This comprehensive evaluation provides evidence to inform global, regional, and national efforts toward preventing and controlling zoonotic events to optimize the health of people, animals, and the environment.

Limitations of the study

One of the limitations of this study is that the dataset used was constructed only from English language databases, and information in other languages could not be searched and used. One opportunity for expansion of this work could be to incorporate non-English-language databases, as information in other languages could not be integrated, especially from governmental databases where English is not an official working language. In addition, recent data were not available from some of the databases or some LICs; therefore, we interpolated the countries with missing data based on economic situation, which may bias the calculation of the GOHI score. Moreover, we found that some datasets were underreported, resulting in high GOHI scores, e.g., in the LICs. This may be due to limited healthcare resources and heavy workloads in LICs, lack of proper awareness of reporting requirements among healthcare providers, and inadequate reporting systems.[63–65]

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

- KEY RESOURCES TABLE
- RESOURCE AVAILABILITY
  - ○ Lead contact
  - ○ Materials availability
  - ○ Data and code availability
- METHOD DETAILS
  - ○ Framework formulation and dataset collection
  - ○ Indicator selection and database building
  - ○ Weight determination and calculation of indicator scores
  - ○ Visualization and correlation analyses
  - ○ Multiple linear regression and multicollinearity test

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2024.109297.

ACKNOWLEDGMENTS

We thank experts from the World Health Organization, the World Organization for Animal Health, the Food and Agriculture Organization, and the World Bank, who critically commented on the analysis and interpretation of the data. The views expressed are those of the author(s) and not necessarily those of the WHO, the WOAH, the FAO, or the WB. Financial support for this study came in part from the Bill & Melinda Gates Foundation (no. INV-046218), the Shanghai Jiao Tong University Integrated Innovation Fund (no. 2020-01), and the International Joint Laboratory on Tropical Diseases Control in Greater Mekong Subregion (no. 21410750200). The sponsor played no role in the study design; in the collection, analysis, or interpretation of the data; in the writing of the report; or in the decision to submit the article for publication.

AUTHOR CONTRIBUTIONS

Design and supervision: K.K., J.-H.C., and Y.Z. Data collection and processing: Z.-S.S., E.-Y.W., Y.L.A., H.-Q.Z., J.-X.Y., T.-G.J., Q.L., and S.-W.F. Data analysis and interpretation: Z.-S.S., X.-C.L., Q.-Y.Z., J.-S.L., S.-Y.G., Z.-Y.G., J.-B.X., L.-F.H., X.-X.Z., S.X., and K.K. Writing – original draft: Z.-S.S., K.K., E.-Y.W., and Y.L.A. Writing – review and editing: L.B.W., S.C.W., M.O., X.-N.Z., Z.-J.W., and X.-K.G. Funding acquisition: X.-N.Z.

DECLARATION OF INTERESTS

The authors declare no competing interests.

Please cite this article in press as: Sun et al., Global One Health index for zoonoses: A performance assessment in 160 countries and territories, iScience (2024), https://doi.org/10.1016/j.isci.2024.109297

Received: September 26, 2023
Revised: December 6, 2023
Accepted: February 16, 2024
Published: March 11, 2024

REFERENCES

1. World Health Organization (2020). Zoonoses. https://www.who.int/news-room/fact-sheets/detail/zoonoses.
2. Centers for Disease Control and Prevention (2021). Zoonotic Diseases. https://www.cdc.gov/onehealth/basics/zoonotic-diseases.html.
3. Centers for Disease Control and Prevention (2019). Zoonotic Diseases Shared Between Animals and People of Most Concern in the U.S.. https://www.cdc.gov/media/releases/2019/s0506-zoonotic-diseases-shared.html#print.
4. Karesh, W.B., Dobson, A., Lloyd-Smith, J.O., Lubroth, J., Dixon, M.A., Bennett, M., Aldrich, S., Harrington, T., Formenty, P., Loh, E.H., et al. (2012). Ecology of zoonoses: natural and unnatural histories. Lancet (London, England) *380*, 1936–1945. https://doi.org/10.1016/s0140-6736(12)61678-x.
5. Salyer, S.J., Silver, R., Simone, K., and Barton Behravesh, C. (2017). Prioritizing Zoonoses for Global Health Capacity Building-Themes from One Health Zoonotic Disease Workshops in 7 Countries, S55-S64. Emerg. Infect. Dis. *23*, S55–S64. https://doi.org/10.3201/eid2313.170418.
6. World bank (2021). Safeguarding Animal, Human and Ecosystem Health: One Health at the World Bank. https://www.worldbank.org/en/topic/agriculture/brief/safeguarding-animal-human-and-ecosystem-health-one-health-at-the-world-bank.
7. Gruber, K. (2021). Preventing zoonotic pandemics: are we there yet? Lancet. Microbe *2*, e352. https://doi.org/10.1016/S2666-5247(21)00187-7.
8. Cupertino, M.D.C., Freitas, A.N.D., Meira, G.S.B., Silva, P.A.M.D., Pires, S.D.S., Cosendey, T.D.A., Fernandes, T.M., Mayers, N.A.J., and Siqueira-Batista, R. (2023). COVID-19 and One Health: potential role of human and animals in SARS-CoV-2 life cycle. Science in One Health *2*, 100017. https://doi.org/10.1016/j.soh.2023.100017.
9. World Health Organization (2017). One Health. https://www.who.int/news-room/questions-and-answers/item/one-health.
10. Ghai, R.R., Wallace, R.M., Kile, J.C., Shoemaker, T.R., Vieira, A.R., Negron, M.E., Shadomy, S.V., Sinclair, J.R., Goryoka, G.W., Salyer, S.J., and Barton Behravesh, C. (2022). A generalizable one health framework for the control of zoonotic diseases. Sci. Rep. *12*, 8588. https://doi.org/10.1038/s41598-022-12619-1.
11. Guo, Z.-Y., Zheng, J., Li, S.-Z., and Zhou, X.-N. (2023). Orientation of One Health development: think globally and act locally. Science in One Health *2*, 100042. https://doi.org/10.1016/j.soh.2023.100042.
12. World Health Organization (2021). One Health High-Level Expert Panel (OHHLEP). https://www.who.int/groups/one-health-high-level-expert-panel.
13. Erkyihun, G.A., and Alemayehu, M.B. (2022). One Health Approach for the Control of Zoonotic Diseases. Zoonoses *2*. https://doi.org/10.15212/zoonoses-2022-0037.
14. Kheirallah, K.A., Al-Mistarehi, A.H., Alsawalha, L., Hijazeen, Z., Mahrous, H., Sheikali, S., Al-Ramini, S., Maayeh, M., Dodeen, R., Farajeh, M., et al. (2021). Prioritizing zoonotic diseases utilizing the One Health approach: Jordan's experience. One Health *13*, 100262. https://doi.org/10.1016/j.onehlt.2021.100262.
15. Centers for Disease Control and Prevention (2022). One Health Zoonotic Disease Prioritization (OHZDP). https://www.cdc.gov/onehealth/what-we-do/zoonotic-disease-prioritization/index.html.
16. Zhang, X.X., Liu, J.S., Han, L.F., Xia, S., Li, S.Z., Li, O.Y., Kassegne, K., Li, M., Yin, K., Hu, Q.Q., et al. (2022). Towards a global One Health index: a potential assessment tool for One Health performance. Infect. Dis. Poverty *11*, 57. https://doi.org/10.1186/s40249-022-00979-9.
17. Zhang, X.X., Liu, J.S., Han, L.F., Simm, G., Guo, X.K., and Zhou, X.N. (2022). One Health: new evaluation framework launched. Nature *604*, 625. https://doi.org/10.1038/d41586-022-01108-0.
18. FAO. Livestock patterns. https://www.fao.org/faostat/en/#data/EK.
19. Qiang, N., Gu, S.-Y., Wang, X.-Y., Zhang, X.-X., Xia, S., Zheng, J.-X., Gong, W.-F., Bergquist, R., Ran, J.-J., and Han, L.-F. (2022). A One Health information database based on standard bibliometric analysis. Sci. One Health *1*, 100012. https://doi.org/10.1016/j.soh.2023.100012.
20. Centers for Disease Control and Prevention (2021). Global Disease Detection (GDD) Operations Center. https://www.cdc.gov/globalhealth/healthprotection/gddopscenter/index.html.
21. Centers for Disease Control and Prevention (2012). Global Health-South Afirca. https://www.cdc.gov/globalhealth/countries/southafrica/what/sargdd-draft1.htm.
22. FAO, OIE, WHO, UN System Influenza Coordination, UNICEF,; The World Bank (2008). Contributing to One World, One Health. https://www.preventionweb.net/files/8627_OWOH14Oct08.pdf.
23. Otu, A., Effa, E., Meseko, C., Cadmus, S., Ochu, C., Athingo, R., Namisango, E., Ogoina, D., Okonofua, F., and Ebenso, B. (2021). Africa needs to prioritize One Health approaches that focus on the environment, animal health and human health. Nat. Med. *27*, 943–946. https://doi.org/10.1038/s41591-021-01375-w.
24. Africa CDC (2020). Framework for One Health Practice in National Public Health Institutes. https://africacdc.org/download/framework-for-one-health-practice-in-national-public-health-institutes/?fbclid=IwAR044d2uPQuNrtrXsSKsKJEOjU6VLp346WsbUH4PnoMrmsly4Raphr6ARBc.
25. Centers for Disease Control and Prevention (2023). Completed OHZDP Workshops. https://www.cdc.gov/onehealth/what-we-do/zoonotic-disease-prioritization/completed-workshops.html.
26. Centers for Disease Control and Prevention (2015). One Health Program. https://www.cdc.gov/globalhealth/countries/southafrica/what/one_health.htm.
27. Alpers, K., Stark, K., Hellenbrand, W., and Ammon, A. (2004). Zoonotic infections in humans. Review of the epidemiological situation in Germany. Bundesgesundheitsbl. - Gesundheitsforsch-. Gesundheitsschutz. *47*, 622–632. https://doi.org/10.1007/s00103-004-0867-7.
28. European Food Safety Authority(EFSA), Amore, G., Boelaert, F., Papanikolaou, A., Rizzi, V., and Stoicescu, A.-V. (2022). Manual for reporting on zoonoses and zoonotic agents, within the framework of Directive 2003/99/EC, and on some other pathogenic microbiological agents for information derived from the year 2021. https://www.efsa.europa.eu/en/supporting/pub/en-7130.
29. Zinsstag, J., Schelling, E., Roth, F., Bonfoh, B., de Savigny, D., and Tanner, M. (2007). Human benefits of animal interventions for zoonosis control. Emerg. Infect. Dis. *13*, 527–531. https://doi.org/10.3201/eid1304.060381.
30. Narrod, C., Zinsstag, J., and Tiongco, M. (2012). A one health framework for estimating the economic costs of zoonotic diseases on society. EcoHealth *9*, 150–162. https://doi.org/10.1007/s10393-012-0747-9.
31. World Health Organization. Zoonotic disease: emerging public health threats in the Region. https://www.emro.who.int/fr/about-who/rc61/zoonotic-diseases.html.
32. Bhatia, R. (2021). Addressing challenge of zoonotic diseases through One Health approach. Indian J. Med. Res. *153*, 249–252. https://doi.org/10.4103/ijmr.IJMR_374_21.
33. Sharan, M., Vijay, D., Yadav, J.P., Bedi, J.S., and Dhaka, P. (2023). Surveillance and response strategies for zoonotic diseases: a comprehensive review. Science in One Health *2*, 100050. https://doi.org/10.1016/j.soh.2023.100050.
34. Medley, A.M., Gasanani, J., Nyolimati, C.A., McIntyre, E., Ward, S., Okuyo, B., Kabiito, D., Bender, C., Jafari, Z., LaMorde, M., et al. (2021). Preventing the cross-border spread of zoonotic diseases: Multisectoral community engagement to characterize animal mobility—Uganda, 2020. Zoonoses Public Health *68*, 747–759. https://doi.org/10.1111/zph.12823.
35. Lin, Z.-R., Li, S.-G., Sun, X.-D., Guo, X.-R., Zheng, Z., Yang, J., Pian, H.-R., Tian, P., Chen, Q.-Y., Sun, X.-Y., et al. (2021). Effectiveness of joint 3 + 1 malaria strategy along China–Myanmar cross border areas. BMC Infect. Dis. *21*, 1246. https://doi.org/10.1186/s12879-021-06920-z.
36. USAID. Partnering for a More Secure World. https://www.usaid.gov/global-health/health-areas/global-health-security/partnering.
37. Rahman, M.T., Sobur, M.A., Islam, M.S., Ievy, S., Hossain, M.J., El Zowalaty, M.E., Rahman, A.T., and Ashour, H.M. (2020). Zoonotic Diseases: Etiology, Impact, and Control.

Microorganisms *8*, 1405. https://doi.org/10.3390/microorganisms8091405.

38. He, J., Guo, Z., Yang, P., Cao, C., Xu, J., Zhou, X., and Li, S. (2022). Social insights on the implementation of One Health in zoonosis prevention and control: a scoping review. Infect. Dis. Poverty *11*, 48. https://doi.org/10.1186/s40249-022-00976-y.
39. National Research Council (US) Committee on Achieving Sustainable Global Capacity for Surveillance and Response to Emerging Diseases of Zoonotic Origin (2008). In Achieving Sustainable Global Capacity for Surveillance and Response to Emerging Diseases of Zoonotic Origin: Workshop Report (National Academies Press (US) Copyright2008by the National Academy of Sciences. All rights reserved). https://doi.org/10.17226/12522.
40. National Research Council (US) Committee on Achieving Sustainable Global Capacity for Surveillance and Response to Emerging Diseases of Zoonotic Origin (2009). In Sustaining Global Surveillance and Response to Emerging Zoonotic Diseases, G.T. Keusch, M. Pappaioanou, M.C. Gonzalez, K.A. Scott, and P. Tsai, eds. (National Academies Press (US) Copyright2009by the National Academy of Sciences. All rights reserved). https://doi.org/10.17226/12625.
41. Wolfe, N.D., Dunavan, C.P., and Diamond, J. (2007). Origins of major human infectious diseases. Nature *447*, 279–283. https://doi.org/10.1038/nature05775.
42. Taylor, L.H., Latham, S.M., and Woolhouse, M.E. (2001). Risk factors for human disease emergence. Philos. Trans. R. Soc. Lond. B Biol. Sci. *356*, 983–989. https://doi.org/10.1098/rstb.2001.0888.
43. Colella, V., Wongnak, P., Tsai, Y.-L., Nguyen, V.-L., Tan, D.Y., Tong, K.B.Y., Lu, N., Fang, F., Zhijuan, Y., Wang, J., et al. (2022). Human social conditions predict the risk of exposure to zoonotic parasites in companion animals in East and Southeast Asia. Commun. Med. *2*, 144. https://doi.org/10.1038/s43856-022-00210-8.
44. Tollefson, J. (2020). Why deforestation and extinctions make pandemics more likely. Nature *584*, 175–176. https://doi.org/10.1038/d41586-020-02341-1.
45. Global Forest Watch (2022). Global primary forest loss. https://www.globalforestwatch.org/dashboards/global/.
46. Zhang, L., Rohr, J., Cui, R., Xin, Y., Han, L., Yang, X., Gu, S., Du, Y., Liang, J., Wang, X., et al. (2022). Biological invasions facilitate zoonotic disease emergences. Nat. Commun. *13*, 1762. https://doi.org/10.1038/s41467-022-29378-2.
47. Jones, B.A., Grace, D., Kock, R., Alonso, S., Rushton, J., Said, M.Y., McKeever, D., Mutua, F., Young, J., McDermott, J., and Pfeiffer, D.U. (2013). Zoonosis emergence linked to agricultural intensification and environmental change. Proc. Natl. Acad. Sci. USA *110*, 8399–8404. https://doi.org/10.1073/pnas.1208059110.
48. Bartlett, H., Holmes, M.A., Petrovan, S.O., Williams, D.R., Wood, J.L.N., and Balmford, A. (2022). Understanding the relative risks of zoonosis emergence under contrasting approaches to meeting livestock product demand. R. Soc. Open Sci. *9*, 211573. https://doi.org/10.1098/rsos.211573.
49. Qian, J., Wu, Z., Zhu, Y., and Liu, C. (2022). One Health: a holistic approach for food safety in livestock. Science in One Health *1*, 100015. https://doi.org/10.1016/j.soh.2023.100015.
50. (2022). Environmental Performance Index. https://epi.yale.edu/epi-results/2022/component/epi.
51. Dorien Braam, M.M., Scissa, C., and Abel, J. (2023). Climate change, migration, and zoonoses in the East and Horn of Africa region: A call for action. https://migrationhealthresearch.iom.int/climate-change-migration-and-zoonoses-east-and-horn-africa-region-call-action.
52. The Lancet Infectious Diseases (2023). Twin threats: climate change and zoonoses. Lancet Infect. Dis. *23*, 1. https://doi.org/10.1016/s1473-3099(22)00817-9.
53. World Health Organization (2022). New report highlights the impact of changes in environment on One Health. https://www.who.int/europe/news/item/01-07-2022-new-report-highlights-the-impact-of-changes-in-environment-on-one-health.
54. Keesing, F., and Ostfeld, R.S. (2021). Impacts of biodiversity and biodiversity loss on zoonotic diseases. Proc. Natl. Acad. Sci. USA *118*, e2023540118. https://doi.org/10.1073/pnas.2023540118.
55. Badker, R., Miller, K., Pardee, C., Oppenheim, B., Stephenson, N., Ash, B., Philippsen, T., Ngoon, C., Savage, P., Lam, C., and Madhav, N. (2021). Challenges in reported COVID-19 data: best practices and recommendations for future epidemics. BMJ Glob. Health *6*, e005542. https://doi.org/10.1136/bmjgh-2021-005542.
56. Catalogue of Bias (2019). Reporting biases. https://catalogofbias.org/biases/reporting-biases/.
57. Bower, J.K., Patel, S., Rudy, J.E., and Felix, A.S. (2017). Addressing Bias in Electronic Health Record-Based Surveillance of Cardiovascular Disease Risk: Finding the Signal Through the Noise. Curr. Epidemiol. Rep. *4*, 346–352. https://doi.org/10.1007/s40471-017-0130-z.
58. Smits, J., and Permanyer, I. (2019). The Subnational Human Development Database. Sci. Data *6*, 190038. https://doi.org/10.1038/sdata.2019.38.
59. Stephens, P.R., Gottdenker, N., Schatz, A.M., Schmidt, J.P., and Drake, J.M. (2021). Characteristics of the 100 largest modern zoonotic disease outbreaks. Philos. Trans. R. Soc. Lond. B Biol. Sci. *376*, 20200535. https://doi.org/10.1098/rstb.2020.0535.
60. Zhao, H.Q., Fei, S.W., Yin, J.X., Li, Q., Jiang, T.G., Guo, Z.Y., Xue, J.B., Han, L.F., Zhang, X.X., Xia, S., et al. (2022). Assessment of performance for a key indicator of One Health: evidence based on One Health index for zoonoses in Sub-Saharan Africa. Infect. Dis. Poverty *11*, 109. https://doi.org/10.1186/s40249-022-01020-9.
61. Zhou, N., Cheng, Z., Zhang, X., Lv, C., Guo, C., Liu, H., Dong, K., Zhang, Y., Liu, C., Chang, Y.F., et al. (2022). Global antimicrobial resistance: a system-wide comprehensive investigation using the Global One Health Index. Infect. Dis. Poverty *11*, 92. https://doi.org/10.1186/s40249-022-01016-5.
62. Liu, J.-S., Li, X.-C., Zhang, Q.-Y., Han, L.-F., Xia, S., Kassegne, K., Zhu, Y.-Z., Yin, K., Hu, Q.-Q., Xiu, L.-S., et al. (2023). China's application of the One Health approach in addressing public health threats at the human-animal-environment interface: Advances and challenges. One Health, 100607. https://doi.org/10.1016/j.onehlt.2023.100607.
63. Konowitz, P.M., Petrossian, G.A., and Rose, D.N. (1984). The underreporting of disease and physicians' knowledge of reporting requirements. Public Health Rep. 99, 31–35.
64. Zhou, D., Pender, M., Jiang, W., Mao, W., and Tang, S. (2019). Under-reporting of TB cases and associated factors: a case study in China. BMC Publ. Health *19*, 1664. https://doi.org/10.1186/s12889-019-8009-1.
65. Gibbons, C.L., Mangen, M.J.J., Plass, D., Havelaar, A.H., Brooke, R.J., Kramarz, P., Peterson, K.L., Stuurman, A.L., Cassini, A., Fèvre, E.M., et al. (2014). Measuring underreporting and under-ascertainment in infectious disease datasets: a comparison of methods. BMC Publ. Health *14*, 147. https://doi.org/10.1186/1471-2458-14-147.
66. Rabozzi, G., Bonizzi, L., Crespi, E., Somaruga, C., Sokooti, M., Tabibi, R., Vellere, F., Brambilla, G., and Colosio, C. (2012). Emerging zoonoses: the "one health approach". Saf. Health Work *3*, 77–83. https://doi.org/10.5491/shaw.2012.3.1.77.
67. Dharmarajan, G., Li, R., Chanda, E., Dean, K.R., Dirzo, R., Jakobsen, K.S., Khan, I., Leirs, H., Shi, Z.-L., Wolfe, N.D., et al. (2022). The Animal Origin of Major Human Infectious Diseases: What Can Past Epidemics Teach Us About Preventing the Next Pandemic? J. Zoonoses *2*. https://doi.org/10.15212/zoonoses-2021-0028.
68. (2020). Emerging zoonoses: A one health challenge. EClinicalMedicine *19*, 100300. https://doi.org/10.1016/j.eclinm.2020.100300.
69. White, R.J., and Razgour, O. (2020). Emerging zoonotic diseases originating in mammals: a systematic review of effects of anthropogenic land-use change. Mamm Rev. *50*, 336–352. https://doi.org/10.1111/mam.12201.
70. Cupertino, M., Resende, M., Mayer, N., Carvalho, L., and Siqueira-Batista, R. (2020). Emerging and re-emerging human infectious diseases: A systematic review of the role of wild animals with a focus on public health. Asian Pac. J. Trop. Med. *13*, 99–106. https://doi.org/10.4103/1995-7645.277535.
71. World Health Organization (2022). One health joint plan of action (2022–2026): working together for the health of humans, animals, plants and the environment. https://www.who.int/publications/i/item/9789240059139.
72. One Health High-Level Expert Panel (2023). One Health action for health security and equity. Lancet (London, England) *401*, 530–533. https://doi.org/10.1016/s0140-6736(23)00086-7.
73. Zinsstag, J., Kaiser-Grolimund, A., Heitz-Tokpa, K., Sreedharan, R., Lubroth, J., Caya, F., Stone, M., Brown, H., Bonfoh, B., Dobell, E., et al. (2023). Advancing One human-animal-environment Health for global health security: what does the evidence say? Lancet *401*, 591–604. https://doi.org/10.1016/S0140-6736(22)01595-1.
74. Mwatondo, A., Rahman-Shepherd, A., Hollmann, L., Chiossi, S., Maina, J., Kurup, K.K., Hassan, O.A., Coates, B., Khan, M., Spencer, J., et al. (2023). A global analysis of One Health Networks and the proliferation of One Health collaborations. Lancet *401*, 605–616. https://doi.org/10.1016/S0140-6736(22)01596-3.
75. Traore, T., Shanks, S., Haider, N., Ahmed, K., Jain, V., Rüegg, S.R., Razavi, A., Kock, R., Erondu, N., Rahman-Shepherd, A., et al. (2023). How prepared is the world? Identifying weaknesses in existing

Please cite this article in press as: Sun et al., Global One Health index for zoonoses: A performance assessment in 160 countries and territories, iScience (2024), https://doi.org/10.1016/j.isci.2024.109297

assessment frameworks for global health security through a One Health approach. Lancet *401*, 673–687. https://doi.org/10.1016/S0140-6736(22)01589-6.

76. Elnaiem, A., Mohamed-Ahmed, O., Zumla, A., Mecaskey, J., Charron, N., Abakar, M.F., Raji, T., Bahalim, A., Manikam, L., Risk, O., et al. (2023). Global and regional governance of One Health and implications for global health security. Lancet *401*, 688–704. https://doi.org/10.1016/S0140-6736(22)01597-5.
77. World Bank (2017). The world by region. https://datatopics.worldbank.org/sdgatlas/archive/2017/the-world-by-region.html.
78. Guo, Z.-Y., Feng, J.-X., Ai, L., Xue, J.-B., Liu, J.-S., Zhang, X.-X., Cao, C.-L., Xu, J., Xia, S., Zhou, X.-N., et al. (2023). Assessment of integrated patterns of human-animal-environment health: a holistic and stratified analysis. Infect. Dis. Poverty *12*, 17. https://doi.org/10.1186/s40249-023-01069-0.
79. World Bank (2023). DataBank. https://databank.worldbank.org/home.aspx.
80. Wolf, M.J., Emerson, J.W., Etsy, D.C., de Sherbinin, A., and Wendling, Z.A. (2022). Environmental Performance Index 2022 (Yale Center for Environmental Law and Policy), pp. 20230628. https://epi.yale.edu/downloads/epi2022report06062022.pdf.
81. World Bank (2021). New World Bank country classifications by income level: 2021-2022. https://blogs.worldbank.org/opendata/new-world-bank-country-classifications-income-level-2021-2022.
82. Ghasemi, A., and Zahediasl, S. (2012). Normality tests for statistical analysis: a guide for non-statisticians. Int. J. Endocrinol. Metab. *10*, 486–489. https://doi.org/10.5812/ijem.3505.
83. Durbin–Watson Test (2008). In The Concise Encyclopedia of Statistics (Springer), pp. 173–175. https://doi.org/10.1007/978-0-387-32833-1_122.
84. Pennsylvania State University (2018). Residuals vs. Fits Plot. https://online.stat.psu.edu/stat462/node/117/.
85. Menard, S. (2002). Applied Logistic Regression Analysis.
86. Obuchi, T., and Kabashima, Y. (2016). Cross validation in LASSO and its acceleration. J. Stat. Mech. *2016*, 053304. https://doi.org/10.1088/1742-5468/2016/05/053304.

Please cite this article in press as: Sun et al., Global One Health index for zoonoses: A performance assessment in 160 countries and territories, iScience (2024), https://doi.org/10.1016/j.isci.2024.109297

STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Weights calculation of GOHI	This paper	Appendix A
Scores calculation of GOHI	This paper	Appendix B
Data sources for GOHI-Zoonoses	This paper	Table 1
Indicator and weight scheme of GOHI-Zoonoses	This paper	Table S1
Country ranking of the GOHI-Zoonoses score	This paper	Table S2
Regional ranking of the GOHI-Zoonoses score	This paper	Table S3
GOHI-Zoonoses gaps in 160 countries/territories	This paper	Table S4
The indicator framework and geographical distribution of the GOHI-Zoonoses scores	This paper	Figure 1
The global scores of GOHI-Zoonoses	This paper	Figure 2
Economic status and regional performance for GOHI-Zoonoses	This paper	Figure 3
Scatterplots and correlation (Spearman's r) between external variables and the GOHI-Zoonoses score	This paper	Figure 4
Scores of each indicator for countries with different economic statuses	This paper	Figure 5
Multiple linear regression and multicollinearity test	This paper	Figures S1–S3
Software and algorithms		
R Studio (version 4.2.3)	R Studio: Integrated development for R	https://posit.co/

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the lead contact, Kokouvi Kassegne (kassegnek@sjtu.edu.cn).

Materials availability

This study did not generate new unique reagents.

Data and code availability

All the data reported in this paper will be shared by the lead contact upon request.

This paper does not report original code.

Any additional information required to reanalyse the data reported in this paper is available from the lead contact upon request.

METHOD DETAILS

Framework formulation and dataset collection

The framework for the GOHI-Zoonoses was formulated as reported previously[60] and is composed of key indicators, subindicators, and datasets.

To establish the GOHI-Zoonoses framework and populate its datasets, we referred to authoritative publicly available databases of the World Health Organization (WHO), World Organization for Animal Health (WOAH), World Bank, Global Health Security Index (GHS index), and Global Health Data Exchange (GHDx).[60] The construction of the dataset was based on the principles of relevance, authoritative sources, open access, completeness, timeliness, comparability, and country-level data.[16] The datasets met the following criteria.

(i) Covered human or animal disease, medical and health data, socioeconomic data, and environmental data related to zoonotic diseases.
(ii) Scientific methods were used to collect the data.
(iii) Covered most countries and territories in the world with sufficient, up-to-date data.

Please cite this article in press as: Sun et al., Global One Health index for zoonoses: A performance assessment in 160 countries and territories, iScience (2024), https://doi.org/10.1016/j.isci.2024.109297

Indicator selection and database building

Key indicators include the source of infection (SI), route of transmission (RT), target population (TP), capacity building (CB), and case studies of zoonotic diseases (referred to as case studies, or CS).[60] Subindicators were established based on our previous study,[60] and datasets were updated according to publicly available databases. We reviewed the literature related to zoonotic diseases and OH,[13,66–70] referred to the One Health Joint Plan of Action (OHJPA)[71] on zoonotic disease actions and OH action for health security and equity,[72–76] and carried out consultations with experts from the WHO, WOAH, Food and Agriculture Organization (FAO), and World Bank. The datasets were divided into qualitative and quantitative data. Qualitative data were marked as "1" when records related to an indicator were found, whereas they were marked as "0" when records related to an indicator were not found.

Weight determination and calculation of indicator scores

The fuzzy analytic hierarchy process (FAHP) algorithm was used to calculate the weights of each indicator, followed by fuzzy comparison matrix formation[16,17] (Appendix A). Weights were averaged across datasets to reduce the impacts of variation between measurements in each dataset. We set the boundary for the missing data rate to be less than 50%,[16] resulting in 160 countries and territories being included. If the number of missing datasets exceeded 160 for any indicator, the indicator was excluded from the calculation.[16] For missing data, we used the average of the corresponding data for the three countries with the most similar sociodemographic characteristics to interpolate the missing values.[17,61] For datasets with a value of 0 or 1, measurements were taken to prevent overpolarization. A positive number was randomly selected from the normal distribution $N \sim (0, 0.16^2)$ to replace the original value 0. A number less than 1 was randomly selected from the normal distribution $N \sim (0, 0.16^2)$ to replace the original value 1.[16] For each value in the datasets, the best/worst value was set and normalized (Appendix B).

Visualization and correlation analyses

Descriptive analysis and data visualization were performed using R 4.2.3 (R Foundation for Statistical Computing, Austria) with R Studio (Posit, USA). Box plots were generated to present GOHI-Zoonoses scores for the seven regions of the world according to the World Bank analytical grouping.[77,78] Ridge and rose plots were generated to show the scores for the five key indicators. A heatmap was generated to show differences between subindicator scores and average scores by country or territory using Excel 2019 (Microsoft, USA).

To explore the relationships between GOHI-Zoonoses and other external sociodemographic, economic, environmental, zoological and climatic factors, datasets related to gross domestic product (GDP) per capita and gross national income (GNI) per capita, life expectancy, population density, the human development index (HDI), and forest area were downloaded from the World Bank database[79], the 2022 Environmental Performance Index,[80] tree cover loss,[45] and livestock density.[18] We classified countries into high-, upper-middle-, lower-middle-, and low-income countries based on their GNI per capita levels from the World Bank.[81] We initially explored the external drivers of GOHI-Zoonoses, and Spearman's rank correlation was calculated to evaluate the correlation between the external factors and GOHI-Zoonoses score. The normality of the data was checked by the Shapiro-Wilk test. The Kruskal-Wallis test was used to analyse differences in GOHI-Zoonoses scores for countries and territories with different income statuses. The significance level α was set to 0.05, which indicated that a P value less than or equal to 0.05 was considered to indicate statistical significance.

Multiple linear regression and multicollinearity test

A multiple linear regression model was initially established between the GOHI-Zoonoses score and GNI, life expectancy at birth, population density, HDI, livestock density, tree cover loss, forest area, and EPI. The residuals were tested for normality using the Kolmogorov-Smirnov method.[82] The Durbin-Watson test was used to test residual independence.[83] A residual scatterplot against the fitted values was generated to test the homogeneity of residual variance.[84] The variance inflation factor (VIF) was subsequently used to test for multicollinearity.[85] If the value of the variable VIF was ≥ 10, LASSO regression and k-fold cross-validation were used to find the lambda value that produced the minimum test mean square error (MSE) and construct the regression model.[86] Variables with regression coefficients that were not zero were selected from the LASSO regression model and included in the multiple linear regression model, which was ultimately analysed to identify external variables affecting the GOHI-Zoonoses score.