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FULL-LENGTH RESEARCH ARTICLE

The Roles of Health System Capacity and Infrastructure in the Associations of Cognitive Human Capital, Wealth, and Health Expenditure with Subjective Well-Being: A Cross-National Path Analysis

RICO LANGE¹ · DAVID BECKER¹ · HEINER RINDERMANN^{1,*}

¹ Department of Psychology, Chemnitz University of Technology, Wilhelm-Raabe-Str. 43, D-09107 Chemnitz, Germany

* Corresponding author: heiner.rindermann@psychologie.tu-chemnitz.de

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Abstract

This study examined whether health-related resources and infrastructure help explain cross-national differences in subjective well-being. Using a country-level dataset covering up to 218 countries and political entities, with construct-specific coverage varying, we estimated theory-guided path models linking cognitive human capital, wealth, health expenditure, access to water and sanitation, and health system capacity with two indicators of subjective well-being: happiness and life satisfaction. The analysis used temporally aggregated indicators from secondary data sources and applied structural equation modeling with full information maximum likelihood to retain partially observed cases. Cognitive human capital was positively associated with wealth ($\beta = .67$), and greater levels of both cognitive human capital and wealth were associated with higher health expenditure ($\beta = .20-.46$). Health expenditure showed significant positive direct associations with both subjective well-being indicators ($\beta = .27-.55$). Wealth had a significant positive direct association only with happiness ($\beta = .44$), whereas cognitive human capital showed such an association only with life satisfaction ($\beta = .34$). Access to water and sanitation was positively associated with cognitive human capital and health expenditure ($\beta = .23-.37$), while health system capacity was positively associated with cognitive human capital and wealth ($\beta = .14-.60$). Model-implied indirect effects suggested that health expenditure, access to water and sanitation, or both partly explained the associations of cognitive human capital and wealth with subjective well-being. The study contributes by distinguishing health expenditure, health infrastructure, and health system capacity as separate macro-level pathways rather than a single health construct.

Keywords: cognitive competences; cognitive capital; health; subjective well-being; cross-national

Sustainable Development Goals (SDGs): SDG 3: Good Health and Well-Being

1. Introduction

Subjective well-being is increasingly used as a national-level indicator of social progress because it captures how people evaluate and experience their lives beyond purely economic measures. The Organisation for Economic Co-operation and Development (OECD, 2025, p. 12) defines subjective well-being as “good mental states, including all of the various evaluations, positive and negative, that people make of their lives and the affective reactions of people to their experiences.” Its core components include life evaluation, affective experiences, and eudaimonic aspects of well-being, such as autonomy, meaning,

and purpose in life (OECD, 2025). These dimensions are shaped by individual circumstances and by the economic, institutional, health-related, and cultural environments in which people live. The present study examines country-level differences in two evaluative measures: happiness and life satisfaction. Here, happiness denotes the World Happiness Report's Cantril ladder, rather than a measure of affective experience.

Subjective well-being is also relevant to national development. People with higher levels of subjective well-being tend to remain with their employers longer and, if unemployed, are more likely to search for new employment (Piekałkiewicz, 2017). Because subjective well-being is associated with intrinsic motivation (Ryan et al., 2022), happier people may be more inclined to seek challenges, improve their skills, and learn (Ryan & Deci, 2000). These processes may enhance company productivity and contribute to economic growth (Burhan et al., 2023). Thus, subjective well-being is not only an outcome of living conditions but also a construct with potential economic and social relevance.

Cognitive human capital is a theoretically important resource for understanding these cross-national differences. It refers to the population-level stock of cognitive competencies that support learning, problem solving, knowledge use, innovation, institutional functioning, and adaptation to complex social and economic conditions. Following Rindermann (2018, p. 43), cognitive human capital "comprises the ability to think (intelligence), knowledge (the store of true and relevant knowledge) and the intelligent use of this knowledge." It is related to, but not identical with, formal education. Education refers primarily to schooling and credentials, whereas cognitive human capital concerns the competencies and knowledge that individuals and populations can apply in economic, institutional, technological, and health-related contexts. It is also distinct from social capital, which concerns networks, trust, and norms of cooperation rather than cognitive competencies themselves.

The idea that education and abilities constitute a form of capital can be traced back to Adam Smith. Smith described the acquisition of skills as a type of fixed capital embodied in individuals, emphasizing that education requires real costs that are "realized" in the person (Smith, 1776/1904, Book II, Chapter I, p. 240). This early insight laid the groundwork for later theories conceptualizing human abilities as investments yielding measurable returns. Building on this foundation, the cognitive capital theory advanced by Hanushek and Woessmann (2015), Lynn and Vanhanen (2002), and Rindermann (2012, 2018) places greater emphasis on cognitive competencies as population-level resources.

The proposed framework links cognitive human capital with subjective well-being through national wealth and health-related conditions. Cognitive competencies support the learning, problem solving, technical expertise, and administrative coordination involved in economic activity and the organization of health services and basic infrastructure. These processes provide a theoretical basis for examining both direct associations with well-being and indirect associations through economic and health-related resources.

In addition to cognitive human capital, health and income are important factors associated with the subjective well-being of a country's population. Higher income enables individuals to meet basic needs and pursue personal goals (Diener et al., 2010), whereas good health, or improvements in health, enables people to work, increase productivity, and participate successfully in their communities (Aydan et al., 2022). At the cross-national level, previous research has found positive associations among cognitive human capital, countries' health characteristics, income or wealth, and subjective well-being (e.g., Burhan et al., 2023; Kundu et al., 2024; Nordheim & Martinussen, 2020).

Previous cross-national studies have included health expenditure as a predictor of subjective well-being (e.g., Kundu et al., 2024; Nordheim & Martinussen, 2020). Expenditure alone, however, does not indicate how financial resources are reflected in health-related conditions. The present study therefore distinguishes health expenditure as a resource input from access to water and sanitation and health system capacity as infrastructural and service-related conditions. Access to water and sanitation represents basic infrastructure that reduces exposure to disease and supports everyday functioning; improvements in these services reduce the occurrence and spread of diseases and infections (e.g., Strunz et al., 2014; Wolf et al., 2022; World Health Organization [WHO], 2023). Health system capacity represents the availability of medical personnel and infrastructure needed to deliver care. This distinction matters because countries

with similar relative allocations to health may differ substantially in infrastructure access and service capacity.

Using country-level data, the study examines whether these distinct health-related conditions help account for the associations of cognitive human capital and national wealth with aggregate subjective well-being.

This study contributes to the literature in three ways. First, it brings cognitive human capital, national wealth, and health-related conditions into a theory-guided cross-national path framework. Second, it distinguishes health expenditure, access to water and sanitation, and health system capacity rather than treating health as a single construct. Third, it compares happiness and life satisfaction to examine whether the same macro-level pathways characterize two evaluative measures of well-being. Together, these distinctions clarify how cognitive and economic resources are associated with national well-being through different health-related pathways.

2. Conceptual Framework: Cognitive Human Capital, Health-Related Resources, and Subjective Well-Being

The conceptual framework specifies theoretically motivated pathways linking cognitive human capital with national wealth, health-related resources, infrastructure, health system capacity, and subjective well-being. It draws on the proposition that cognitive competencies support the production, organization, and effective use of economic and institutional resources, which in turn shape health-related conditions and population well-being. The directional paths are theory-guided cross-national associations; because the data are observational and temporally aggregated, they do not establish causal effects and do not exclude reverse or reciprocal relationships.

Cognitive ability contributes to job performance, particularly in cognitively complex occupations. It supports the understanding of concepts and causal relationships, promoting insight, foresight, and rationality (Rindermann, 2018, p. 188). These capacities facilitate the management of complexity in companies and public administration and support more efficient, goal-oriented action. They also provide a foundation for technological innovation and the adoption of technologies developed in other countries. Cognitive ability is relevant to political and institutional characteristics, including democracy, the rule of law, political liberty, government effectiveness, and human rights, which can impede or support economic development (Rindermann & Carl, 2020). Together, these pathways link cognitive ability (i.e., cognitive human capital) with national economic development. Past research has documented positive associations between cognitive ability and gross domestic product at the cross-country level (e.g., Boman, 2024; Burhan et al., 2014; Rindermann, 2018).

As a country's economy grows, higher incomes can help people meet their needs and pursue personal goals, potentially enhancing their subjective well-being (Diener et al., 2010). Oparina et al. (2025) found that income had no significant effect on happiness in rich countries after controlling for social variables, whereas such an effect was observed in low-income countries. These findings are consistent with the Easterlin Paradox (Easterlin, 1974), which suggests that increases in income do not necessarily raise subjective well-being. There may be a threshold at which additional increases in population income no longer have a positive direct effect on subjective well-being at the country level (Burhan et al., 2023).

As national income grows, for instance through an increase in cognitive human capital, countries may be able to allocate more funds to sectors such as health care, which may, in turn, foster people's subjective well-being. Analyses by Nordheim and Martinussen (2020) and Aydan et al. (2022), both based on OECD country samples, indicated a positive association between health care spending and subjective well-being. Kundu et al. (2024) also found a significant positive relation between health expenditure per capita and happiness in low-income countries, but a non-significant association in high-income countries, after controlling for life expectancy, democratic quality, inflation, unemployment, and the Gini index. However, the effect of health expenditure on happiness may be mediated by other factors (e.g., life expectancy) that were included as control variables in their regression analysis.

Health system capacity and access to improved water and sanitation may be plausible mediators of the effects of health expenditure because they represent proximal factors that affect health outcomes.

Wealthier countries are more likely to possess the financial, material, organizational, and human resources needed to adapt health system capacity to population needs and to expand or improve access to water and sanitation. Past research has shown that countries' gross domestic product, as an indicator of national wealth, is positively associated with indicators of health system capacity, such as physicians per capita (e.g., Cooper et al., 2003; Liu et al., 2017) and hospital beds per capita (e.g., Sen-Crowe et al., 2021), as well as with access to water and sanitation (e.g., Achuo & Asongu, 2025; Ando et al., 2025). Greater health system capacity represents a larger supply of physicians and hospital beds. These indicators capture service availability, rather than directly measuring the quality or efficiency of care.

In addition, both during their education and throughout their professional careers, medical professionals are confronted with cognitively complex issues that must be understood and, when necessary, solved. The same applies to the development of new medications, treatment methods, and improved medical technology. Furthermore, the development, installation, and maintenance of water and sanitation services depend on technical expertise, managerial capacity, and trained personnel (e.g., WHO, 2026). For these and related activities, cognitive ability may be essential because it is positively associated with educational and training success and job performance, and its importance tends to increase as task complexity rises (e.g., Sackett et al., 2024; Salgado & Moscoso, 2019).

Beyond national wealth and health characteristics, numerous additional pathways may connect cognitive ability to population well-being, including freedom, democracy, crime, and modernization (e.g., Lynn & Vanhanen, 2012; Stolarski et al., 2015; Veenhoven & Choi, 2012). Accordingly, at the cross-national level, cognitive human capital may affect subjective well-being primarily through indirect, mediating pathways rather than through a direct effect (Veenhoven & Choi, 2012). However, a positive direct effect on subjective well-being may still emerge if not all relevant mediators are incorporated into the model.

Health expenditure, access to water and sanitation, and health system capacity thus represent financial allocation, basic infrastructure, and service capacity, respectively. The framework examines how cognitive and economic resources are associated with each of these conditions and how those conditions, in turn, are associated with national subjective well-being.

Based on the theoretical framework and empirical results presented above, the following theory-guided pathways are examined within a path-modeling framework (see Figure 1).

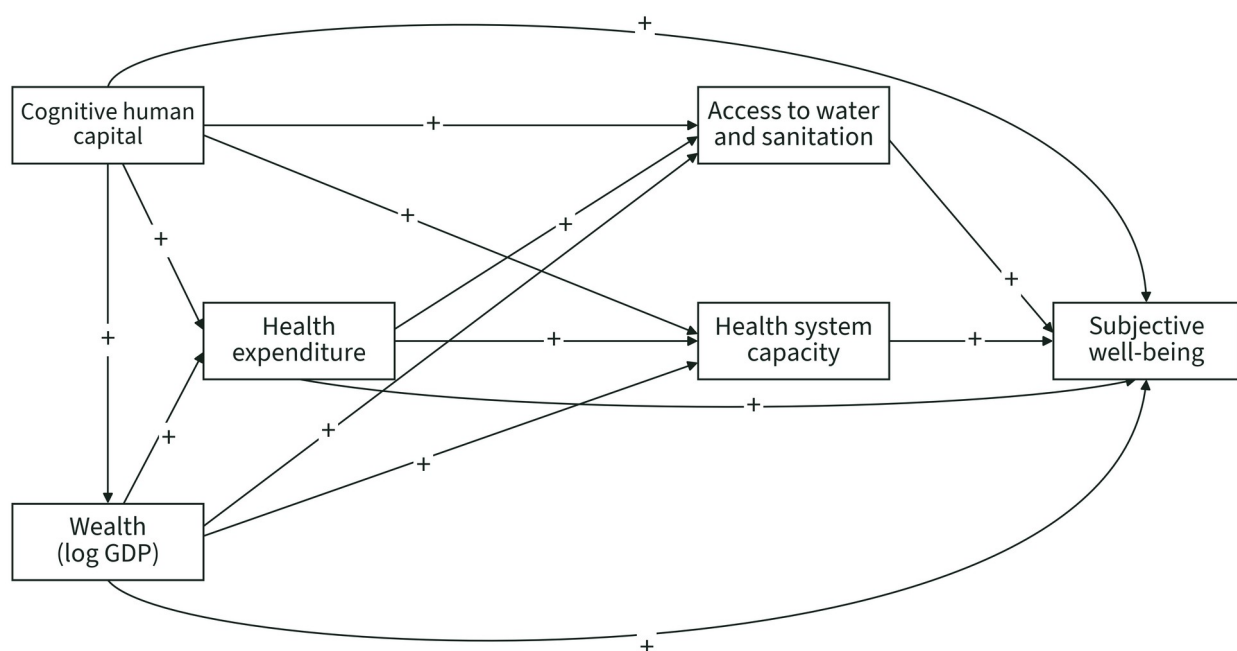


Figure 1. The expected relationships between cognitive human capital, wealth, health-related variables, and subjective well-being

Note. Plus signs indicate hypothesized positive associations. Wealth represents GDP per capita in purchasing power parity, transformed using the natural logarithm as $\log(\text{GDP per capita (PPP)} + 1)$ before aggregation.

Cognitive human capital is hypothesized to be positively associated with national wealth, health expenditure, health system capacity, access to water and sanitation, and subjective well-being. Cognitive human capital is also expected to be indirectly associated with health expenditure through national wealth and indirectly associated with subjective well-being through health expenditure, health system capacity, and access to water and sanitation. National wealth is expected to follow similar pathways to subjective well-being. Health expenditure is specified in the theory-guided model as being positively associated with health system capacity and access to water and sanitation because the expansion and maintenance of these systems require financial resources and administrative capacity. Finally, health expenditure, health system capacity, and access to water and sanitation are expected to be positively associated with subjective well-being.

The integrated framework therefore examines the direct and indirect associations linking these distinct health-related conditions with national subjective well-being.

3. Methods

3.1 Data Sources, Unit of Analysis, and Construction of the Analytic Dataset

The unit of analysis was the country or political entity. The analytic dataset combined secondary country-level indicators from publicly available international data sources. Cognitive human capital was derived from international large-scale educational assessment data, including PISA (OECD, 2026), TIMSS (International Association for the Evaluation of Educational Achievement [IEA], 2025) and PIRLS (IEA, 2023). Health-related indicators, including access to drinking water, sanitation access, physicians per 1,000 people, hospital beds per 1,000 people, and health expenditure, were obtained from the World Factbook (Central Intelligence Agency [CIA], n.d.) via archived versions. Subjective well-being was represented by two country-level indicators: happiness from the World Happiness Report (Helliwell et al., 2025) and life satisfaction based on the World Values Survey-derived factor scores reported by Becker et al. (2024). National wealth was measured using GDP per capita in purchasing power parity from the World Bank's World Development Indicators (World Bank, 2026).

The dataset was constructed by harmonizing ISO-ALPHA-3 country codes, aligning countries and political entities across sources, transforming variables where required, and aggregating available observations to the country level. Repeated observations were averaged after transformation. Each World Factbook indicator contributed its most recent reported observation for each country. The resulting measures summarize country-level differences across the source-specific periods in Table 1.

The analytic dataset comprised 218 countries and political entities. Observed counts for the main analytic variables are reported in Tables 1 and A2; Table A1 presents the individual indicators. Full information maximum likelihood (FIML) incorporated the available observations in the structural models.

Each country or political entity contributed one aggregated record. The aggregation combined information from international assessment cycles, survey waves, and archived World Factbook observations.

Because the source systems differ in timing and coverage, the analytic variables are not strictly contemporaneous. GDP and World Happiness Report scores are aggregated across available years, cognitive human capital combines multiple assessment cycles, the WVS-based life-satisfaction score reflects different survey waves, and World Factbook indicators use the most recent reported country observations. The resulting measures should therefore be interpreted as temporally smoothed cross-national indicators rather than as a synchronized country-year panel. A restricted common-window sensitivity analysis was not used because the key constructs do not share a common country-year structure; restricting the sample on the timing of a single indicator would alter country coverage and the missing-data structure rather than isolate temporal coverage.

Table 1. Overview of data sources, time coverage, and country-level construction

Construct	Indicators	Main source	Time coverage/waves	Country-level construction	Available <i>N</i>
Cognitive human capital	PISA, TIMSS, and PIRLS domain-level achievement indicators	OECD; IEA	2000–2023, depending on assessment cycle	Standardized domain-level indicators were aggregated within assessment and domain and then used to estimate country-level cognitive human capital scores	113 combined; source-indicator <i>N</i> in Table A1: 24–81
Health expenditure	Health expenditure (% of total government expenditure)	World Factbook via archived versions	Most recent available observation	Separate relative-allocation measure; higher values indicate a larger share of the government budget allocated to health	199
Access to water and sanitation	Drinking water access; sanitation access	World Factbook via archived versions	Most recent available observations	Standardized indicators were aggregated into a country-level access to water and sanitation composite	205 combined (203–207 per indicator)
Health system capacity	Physicians per 1,000 people; hospital beds per 1,000 people	World Factbook via archived versions	Most recent available observations	Standardized indicators were aggregated into a country-level health system capacity composite	209 combined (158–205 per indicator)
Wealth	GDP per capita (PPP)	World Bank World Development Indicators	Annual data (2000–2024)	Yearly GDP per capita (PPP) values were transformed as $\log(\text{GDP per capita (PPP)} + 1)$ and then averaged to obtain a country-level wealth indicator	201 combined and filtered; annual source <i>N</i> in Table A1: 236–247
Happiness	Cantril ladder / World Happiness Report country scores	World Happiness Report	Source-labeled years 2011–2025; 2013 absent	Available country scores were compiled and averaged to obtain a country-level happiness indicator	169 (137–158 per wave)
Life satisfaction	WVS-derived life satisfaction factor score	Becker et al. (2024), based on the World Values Survey	WVS waves used in the source study; country participation varies by wave	Country-level factor scores were retained as the life satisfaction indicator	100

Note. *N* denotes observed country-level coverage of the final analytic variable. Parenthetical ranges give source-indicator coverage before aggregation and filtering; regional aggregates, such as OECD members, were excluded from the analytic dataset. Cognitive source-indicator counts range from 24 to 81, and annual GDP source counts range from 236 to 247 (Table A1). Repeated observations were averaged after transformation; World Factbook indicators use the most recent reported country observation. Observation periods differ across sources and countries.

3.2 Software, General Analytical Framework, and Standardization Procedures

Analyses were conducted in R (Version 4.0.0; R Core Team, 2020). The psych package was used for reliability analyses and exploratory factor analysis (Revelle, 2023), lavaan for confirmatory factor analysis and path models (Rosseel, 2012), and nFactors to support exploratory factor-retention decisions (Raïche & Magis, 2020).

Indicators measured on different scales were z-standardized before composite construction. Averaging standardized indicators places them on a common numerical scale and gives each available indicator equal weight within its composite. Fully standardized path coefficients are reported to express conditional associations in standard-deviation units (Cohen et al., 2003; Keith, 2015).

Domain composites were formed by averaging available standardized achievement indicators within each assessment domain. Access to water and sanitation combined drinking-water and sanitation indicators, and health system capacity combined physician and hospital-bed densities. Cognitive domain composites served as indicators in the CFA; the resulting cognitive factor scores and the health-related composites were subsequently used as observed inputs in the path models.

GDP per capita was log-transformed before temporal aggregation to reduce skewness (Field, 2018); its exact transformation is specified below.

3.3 Reliability Assessment, Missing Data, and Model Specifications

Reliability analyses and exploratory factor analysis (EFA) assessed the internal consistency and factor structure of the indicator sets. Cronbach's alpha (Cronbach, 1951) and McDonald's omega (McDonald, 1999) provided complementary reliability estimates (Revelle & Zinbarg, 2009). Hierarchical omega (ω_h) estimates the proportion of variance in a composite score attributable to a general factor. Explained common variance (ECV) instead refers to the proportion of common variance attributable to that factor.

EFA and reliability analyses informed the construction of the indicator sets. A CFA of the cognitive domain composites provided country-level cognitive human capital scores. The two path models then treated these scores and the other country-level variables as observed inputs, with paths specified by the conceptual framework in Section 2. The measurement analyses informed construct construction, not the selection of structural paths.

The cognitive CFA used maximum likelihood with robust standard errors (MLR; Yuan & Bentler, 2000). Both structural path models used maximum likelihood (ML), with full information maximum likelihood (FIML) for incomplete observations (Enders & Bandalos, 2001). FIML relies on the missing-at-random assumption and a correctly specified model. For the ML/FIML path models, standard errors were obtained from the observed information matrix; standard errors for defined indirect and total associations used the delta method.

Observed variables were standardized for model estimation, and exogenous-variable means and variances were freely estimated. Results report fully standardized path coefficients, their statistical significance, indirect and total associations, and the proportion of outcome variance explained within each model. Positive directional hypotheses were evaluated using one-tailed tests. For the negative water-and-sanitation pathways, one-tailed tests assessed associations in the negative direction, not support for the hypothesized positive relationships. Residual correlations were evaluated using two-tailed tests. Comparisons across outcomes are descriptive: differences in coefficient magnitudes or significance levels do not, by themselves, establish statistically significant differences between the two models.

The cognitive measurement model was evaluated using the Comparative Fit Index (CFI) and Root Mean Square Error of Approximation (RMSEA) (Hu & Bentler, 1999). The Tucker–Lewis Index (TLI) and Standardized Root Mean Square Residual (SRMR) are also reported for the structural models.

Indirect associations were calculated by multiplying the coefficients along each specified pathway. Total associations combined the direct coefficient with all corresponding indirect components.

3.4 Cognitive Human Capital (Cognitive Ability)

Cognitive human capital was derived from country-level performance in the Programme for International Student Assessment (PISA; OECD, 2026), the Trends in International Mathematics and Science Study (TIMSS; IEA, 2025), and the Progress in International Reading Literacy Study (PIRLS; IEA, 2023). Assessment cycles and indicator coverage are detailed in Table A1 (Appendix A).

The use of these assessments reflects the cognitive ability component of human capital (Rindermann, 2018). National PISA and TIMSS scores have shown strong convergence, with correlations of .82–.83 for aggregate scores (Rindermann, 2007) and .923 for mathematics and .926 for science in 2015 (Klieme, 2016). Brown et al. (2005) reported correlations of .94–.96 among national PISA domain medians and .50–.68 between PIRLS reading and PISA/TIMSS domains across 21 countries. Together, these findings support their use as related indicators covering reading, mathematics and science. International achievement scores also have an established role in measuring cognitive ability and examining their associations with economic development (Angrist et al., 2021; Hanushek & Kimko, 2000; Hanushek & Woessmann, 2012). Student achievement studies are reliable and valid measures of cognitive ability among populations at both the individual and societal levels (Rindermann, 2025a, 2025b, 2026).

Domain-specific composites were calculated by averaging available standardized indicators within each assessment and domain, including PISA mathematics assessments from 2000 to 2022. These composites served as the observed indicators in the cognitive CFA.

The achievement-indicator set showed very high internal consistency (Cronbach's $\alpha \approx .96$; standardized $\alpha = .99$). Hierarchical omega was .85, with approximately 75% of the common variance attributable to the general factor. The first exploratory eigenvalue (35.7) was substantially larger than the next two (9.2 and 3.0), indicating a dominant general component. All indicators loaded significantly on the latent factor in the one-factor CFA, with stronger standardized loadings of .98–1.00 and other loadings of .63–.90. The model nevertheless showed poor global fit (CFI = .72; RMSEA = .53).

Factor scores were extracted for 113 countries and used as an observed summary of shared cognitive performance in the path models. The scores summarize a dominant general component, but the one-factor model did not adequately fit the covariance structure.

3.5 Health-Related Resources, Infrastructure, and Capacity

Health-related indicators represented financial allocation, basic infrastructure, and service capacity. Drinking-water access, sanitation access, physicians per 1,000 people, and hospital beds per 1,000 people were obtained from archived World Factbook data (CIA, n.d.; Table A1).

The selection follows the study's focus on health-related conditions as intermediate pathways linking cognitive human capital and national wealth with subjective well-being.

For the combined health-indicator set, alpha estimates ranged from .77 to .85, hierarchical omega was .90, and the general factor accounted for approximately 70% of the common variance.

The first exploratory eigenvalue was 2.21. The indicators were organized into two conceptually distinct composites: access to water and sanitation, and health system capacity.

The water and sanitation composite combined access to improved drinking water and sanitation and was available for 205 countries. The health system capacity composite combined physician and hospital-bed densities and was available for 209 countries. Each composite was calculated by averaging its available standardized component indicators.

Health expenditure was analyzed as the percentage of total government expenditure allocated to health ($N = 199$; CIA, n.d.; Table A2). Higher values indicate a larger health-budget share. Higher water and sanitation scores indicate broader access, and higher capacity scores indicate greater physician and hospital-bed availability.

3.6 Subjective Well-Being (SWB) and Wealth

Subjective well-being was represented by two life-evaluation measures from different sources: the World Happiness Report's Cantril ladder and the WVS-derived life satisfaction factor. The measures differ in question wording, survey context, and country coverage. Separate models allowed their country-level associations to be compared without treating the measures as interchangeable.

The World Happiness Report measure asks respondents to rate their current life from 0 (worst possible life) to 10 (best possible life; Helliwell et al., 2025). Available country-ranking scores were averaged to obtain an indicator for 169 countries. This variable is referred to as happiness throughout the article. Survey reference periods can overlap across country-ranking scores (Tables 1 and A1).

The second indicator was based on the Life Satisfaction factor reported in Becker et al. (2024), which relies on data from the World Values Survey (WVS). In that study, *life satisfaction* was constructed within a broader factor-analytic framework applied to attitudinal items. Specifically, three items reflecting subjective evaluations of life satisfaction were identified and formed a distinct factor in exploratory factor analyses. These items loaded consistently on a separate dimension, indicating that life satisfaction represents a coherent construct within the broader attitudinal space. Factor scores for this dimension were subsequently estimated at the country level ($N = 100$) and used as an alternative indicator of subjective well-being.

The WVS-derived measure summarizes country-level observations from different survey waves.

Wealth was represented by GDP per capita in purchasing power parity (PPP), obtained from the World Bank's World Development Indicators for 2000–2024 (World Bank, 2026). Available annual values were transformed using the natural logarithm as $\log(\text{GDP per capita (PPP)} + 1)$ and then averaged within countries ($N = 201$). This variable measures economic output per person adjusted for price-level differences.

Table A2 presents GDP per capita in thousands of international dollars; the path models use the transformed measure.

Appendix B presents the model specifications and data-preparation code excerpts; Appendix A provides descriptive statistics, and Appendix C presents correlations.

4. Results

Both path models were saturated ($df = 0$), with CFI = 1.000, TLI = 1.000, RMSEA = .000 and SRMR = .000. These values follow from the saturated specification and are therefore uninformative as evidence of global structural fit; interpretation focuses on the standardized path coefficients, their statistical significance, and explained variance (Kenny et al., 2015; Kline, 2023).

4.1 Path Model 1: Predicting Happiness

Tables A2 and C1 present descriptive statistics and correlations.

The model accounted for 73.6% of the variance in happiness ($R^2 = .736$; Figure 2). Wealth ($\beta = .44$), health expenditure ($\beta = .27$), and access to water and sanitation ($\beta = .26$) each had significant positive direct associations with happiness ($p < .001$; one-tailed tests). Cognitive human capital ($\beta = .06$, $p = .423$) and health system capacity ($\beta = .01$, $p = .093$) did not show significant positive direct associations with happiness (one-tailed tests).

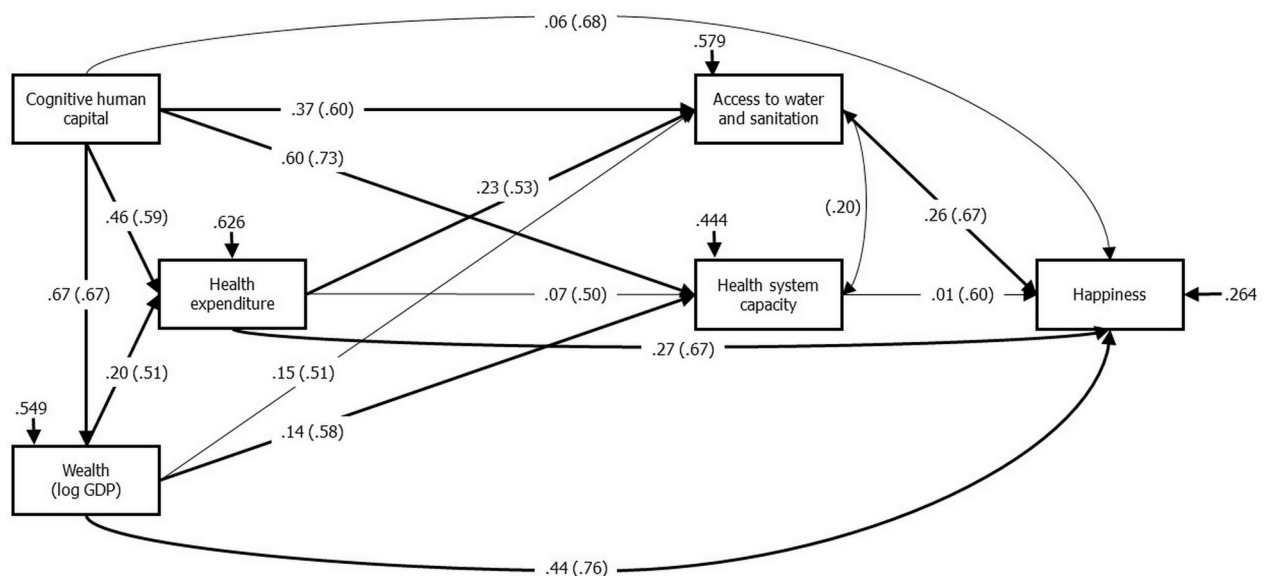


Figure 2. Path model predicting happiness as an indicator of subjective well-being

Note. Single-headed arrows show standardized path coefficients; parentheses give marginal correlations. Bold lines indicate significant structural paths ($p < .05$); regular lines indicate non-significant structural paths. Test directions are specified in the Results. The double-headed arrow shows the residual correlation between water and sanitation access and health system capacity; residual correlations are evaluated with two-tailed tests. Values on arrows entering a variable without an originating variable denote residual variances. Dataset: 218 countries and political entities; Table 1 gives observed counts for each variable. Wealth is the country average of $\log(\text{GDP per capita (PPP)} + 1)$.

Cognitive human capital had a significant positive association with wealth ($\beta = .67$, $p < .05$; one-tailed test). Cognitive human capital and wealth also had significant positive associations with health expenditure ($\beta = .46$ and $.20$, respectively; $p < .05$; one-tailed tests). Access to water and sanitation was significantly positively associated with cognitive human capital ($\beta = .37$) and health expenditure ($\beta = .23$) ($p < .05$; one-tailed tests), but the wealth coefficient (.15) was not significant. Health system capacity had significant positive associations with cognitive human capital ($\beta = .60$) and wealth ($\beta = .14$) ($p < .05$; one-tailed tests), whereas its association with health expenditure was not significantly positive ($\beta = .07$, $p = .459$; one-tailed test).

The total associations with happiness were significantly positive: .68 for cognitive human capital, .55 for wealth, and .32 for health expenditure. Their total indirect components were .62, .10, and .06, respectively. The total indirect associations were significantly positive for cognitive human capital ($p < .001$), wealth ($p = .039$), and health expenditure ($p = .039$; one-tailed tests). Most of the total association for cognitive human

capital therefore arose from indirect components. The indirect components through health expenditure alone were .12 for cognitive human capital and .05 for wealth; both were significantly positive ($p < .05$; one-tailed tests). Totals and components were rounded separately.

Additional significant positive indirect components linked cognitive human capital with happiness through health expenditure and then water and sanitation ($\beta = .03$), through water and sanitation alone ($\beta = .10$), through wealth alone ($\beta = .30$), and through wealth and then health expenditure ($\beta = .04$) ($p < .05$; one-tailed tests). The indirect component from health expenditure through water and sanitation was also significantly positive ($\beta = .06$, $p < .05$; one-tailed test). All remaining indirect components were not significantly positive ($p > .05$; one-tailed tests).

4.2 Path Model 2: Predicting Life Satisfaction

The model accounted for 57.2% of the variance in life satisfaction ($R^2 = .572$; Figure 3). Health expenditure showed a significant positive direct association with life satisfaction ($\beta = .55$, $p < .001$), as did cognitive human capital ($\beta = .34$, $p = .002$; one-tailed tests). Wealth did not show a significant positive direct association ($\beta = .09$, $p = .208$; one-tailed test), and health system capacity ($\beta = .04$) was also not significantly positive. Access to water and sanitation had a significant negative conditional association with life satisfaction ($\beta = -.25$, $p = .019$; one-tailed test in the negative direction), opposite to the hypothesized positive association. Its coefficient for happiness was significantly positive ($\beta = .26$, $p < .001$).

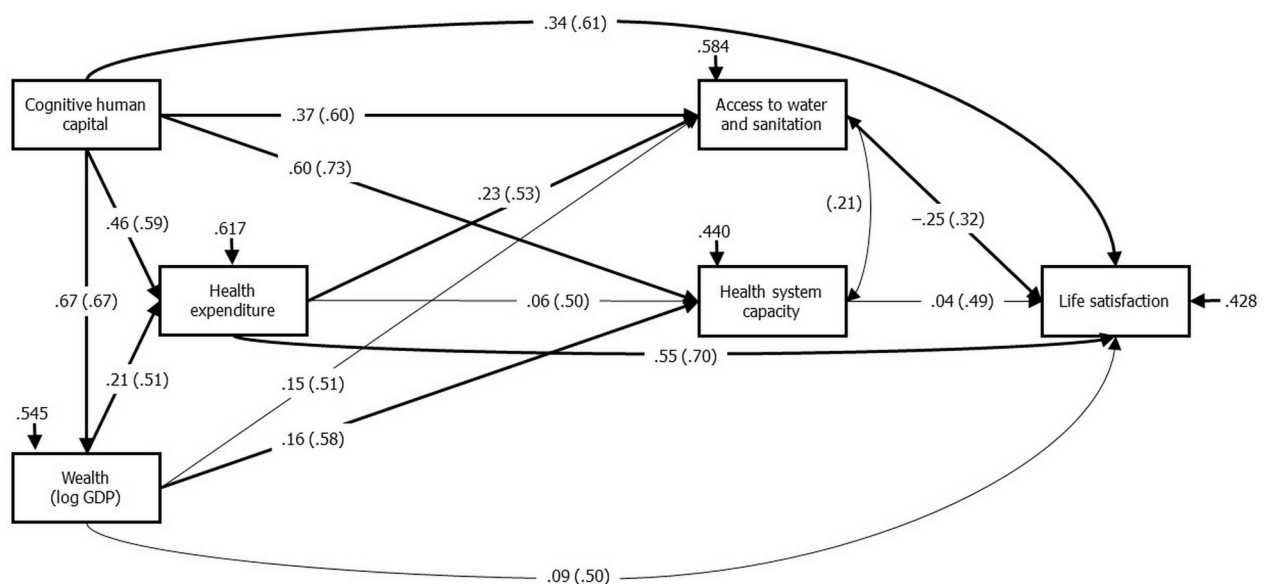


Figure 3. Path model predicting life satisfaction as an indicator of subjective well-being

Note. Single-headed arrows show standardized path coefficients; parentheses give marginal correlations. Bold lines indicate significant structural paths ($p < .05$); regular lines indicate non-significant structural paths. Test directions are specified in the Results. The double-headed arrow shows the residual correlation between water and sanitation access and health system capacity; residual correlations are evaluated with two-tailed tests. Values on arrows entering a variable without an originating variable denote residual variances. Dataset: 218 countries and political entities; Table 1 gives observed counts for each variable. Wealth is the country average of $\log(\text{GDP per capita (PPP)} + 1)$.

Cognitive human capital had a significant positive association with wealth ($\beta = .67$, $p < .05$; one-tailed test). Cognitive human capital and wealth also had significant positive associations with health expenditure ($\beta = .46$ and $.21$, respectively; $p < .05$; one-tailed tests). Access to water and sanitation had significant positive associations with cognitive human capital ($\beta = .37$) and health expenditure ($\beta = .23$) ($p < .05$; one-tailed tests), whereas the wealth coefficient was not significant ($\beta = .15$, $p = .139$). Health system capacity had significant positive associations with cognitive human capital ($\beta = .60$) and wealth ($\beta = .16$) ($p < .05$; one-tailed tests), while the health-expenditure coefficient was not significantly positive ($\beta = .06$, $p = .193$; one-tailed test).

The model-implied total associations with life satisfaction were .61 for cognitive human capital, .50 for health expenditure, and .16 for wealth. The first two total associations were significantly positive ($p < .001$), whereas the positive total association for wealth was not significant ($p = .068$). The total indirect components were .26, $-.05$, and .07 for cognitive human capital, health expenditure, and wealth,

respectively. The total indirect association for cognitive human capital was significantly positive ($\beta = .26$, $p < .05$), while those for wealth ($\beta = .07$, $p = .100$) and health expenditure ($\beta = -.05$, $p = .966$) were not significantly positive (one-tailed tests). Totals and components were rounded separately.

The indirect components through health expenditure alone were significantly positive for cognitive human capital ($\beta = .25$, $p < .001$) and wealth ($\beta = .11$, $p < .05$; one-tailed tests). The component from cognitive human capital through health expenditure and then water and sanitation was significantly negative ($\beta = -.03$, $p < .05$; one-tailed test in the negative direction), whereas the component through wealth and then health expenditure was significantly positive ($\beta = .08$, $p < .05$; one-tailed test). Thus, the indirect decomposition included components with opposing signs.

The indirect component from health expenditure through water and sanitation was significantly negative for life satisfaction ($\beta = -.06$, $p < .05$; one-tailed test in the negative direction), compared with a significant positive component of .06 for happiness. All remaining indirect effects were non-significant ($p > .05$; two-tailed tests). Water and sanitation had a positive marginal correlation with life satisfaction ($r = .32$) despite its negative conditional path coefficient ($\beta = -.25$).

5. Discussion

5.1 Main Findings and Contribution

Cognitive human capital had the largest total association among the three upstream predictors in both models, but the composition of that association differed. For happiness, the total indirect association of cognitive human capital was significantly positive ($p < .001$), as were the total indirect associations of wealth and health expenditure ($p = .039$ for each). For life satisfaction, the total indirect association of cognitive human capital was significantly positive ($p < .05$), whereas those of wealth ($p = .100$) and health expenditure ($p = .966$) were not significantly positive. Indirect pathways accounted for most of the cognitive-human-capital association with happiness, while the direct component was larger for life satisfaction. Distinguishing direct, indirect, and total associations therefore provides a more informative account than considering the direct coefficients alone.

The direct associations also showed different patterns across the models. Wealth had a significant positive association with happiness, but its association with life satisfaction did not reach significance. Cognitive human capital showed the reverse pattern. Health expenditure had significant positive direct associations with both outcomes. Access to water and sanitation had a significant positive conditional association with happiness and a significant negative conditional association with life satisfaction ($p = .019$). Health system capacity did not show a significant positive direct association with either outcome. These findings support examining the health-related dimensions separately, while the cross-model contrasts remain descriptive rather than tests of differences between coefficients.

5.2 Interpretation and Policy Implications

The two outcomes provide related but non-identical perspectives on national life evaluation. Differences in their question wording, survey context, temporal coverage, and observed country coverage are relevant when interpreting the contrasting coefficients. The results therefore show the value of examining more than one evaluative measure, rather than establishing a general distinction between emotional happiness and life satisfaction. For cognitive human capital, the predominance of indirect components in the happiness model also illustrates why a small direct coefficient can coexist with a substantial total association.

The distinction between marginal and conditional associations is particularly important for water and sanitation. Its positive marginal correlation with life satisfaction describes the overall cross-national pattern; its negative path coefficient describes the association after adjustment for the other modeled variables. This sign reversal does not establish that improving water and sanitation reduces well-being. It instead calls for interpreting infrastructure alongside the cognitive, economic, and health-related conditions included in the model. Similarly, the absence of a significant positive direct association for health system capacity does not demonstrate that physicians or hospital beds are unimportant. The capacity indicators measure availability, not the quality, accessibility, or effectiveness of care.

For policy, the findings support coordinated monitoring of cognitive ability, health financing, basic infrastructure, and service capacity. Health expenditure is measured here as a share of total government expenditure, so its coefficient concerns relative budget allocation rather than an absolute increase in spending or spending per person. Reporting this share alongside water and sanitation access, physician and hospital-bed availability, and both life-evaluation measures would make the distinct dimensions visible when development priorities are assessed. The findings provide a basis for such multidimensional assessment, not an estimate of the well-being gain that would follow a particular budget increase or infrastructure intervention.

5.3 Limitations and Future Research

Institutional conditions offer an important extension of the framework. Government effectiveness, voice and accountability, the rule of law, and control of corruption may help explain how cognitive and economic resources are associated with health-sector allocation, infrastructure maintenance, and service delivery (Achuo & Asongu, 2025; Kanyama, 2014; Lv & Xu, 2016). Including these conditions would help distinguish the health-related pathways examined here from additional institutional channels.

The cross-sectional design estimates country-level associations and does not establish temporal ordering or exclude reverse and reciprocal relationships. Institutional quality, inequality, political stability, social trust, cultural values, and demographic structure may also influence these associations. The cognitive measurement model presents a further limitation: evidence of a dominant general component coexists with poor one-factor CFA fit. Using its factor scores as observed inputs does not carry their measurement uncertainty through the structural models. Further work should refine the measurement model and jointly estimate measurement and structural relationships, alongside longitudinal analyses of the proposed pathways.

The findings concern differences between countries and political entities. They do not establish that the same relationships hold between individuals within a country. Individual-level or multilevel analyses are needed to distinguish these levels of association and avoid inferring individual-level relationships from aggregate associations (Robinson, 1950).

The indicators summarize different assessment cycles, survey waves, and observation years. Temporal aggregation provides summary measures of country-level conditions, but the observations are not fully synchronized across countries or constructs. These differences may introduce measurement error and may affect substantive comparisons when older observations differ systematically from more recent ones.

A restricted common-window sensitivity analysis was not feasible because the key constructs do not share a common country-year structure. Restricting the sample on the timing of a single indicator would substantially alter sample composition and the missing-data structure rather than isolate temporal coverage. Future research should examine the robustness of the observed pathways using harmonized panel data or more restricted common-time-window datasets when comparable repeated observations become available.

Extensions should also distinguish physical and mental health services. Psychiatrist and psychologist densities would add a mental health dimension to service capacity (Touburg & Veenhoven, 2015). Health behavior is another relevant pathway: physical activity is associated with better health and lower mortality (Barry et al., 2014; Garcia et al., 2023), and cross-national research links it with happiness (Mangra et al., 2024; Tavares, 2015).

Life expectancy, infant and maternal mortality, and disease burden would extend the model from health resources to population health outcomes. Examining these outcomes alongside subjective well-being would help assess whether health-related resources are associated with measurable health improvements and whether those improvements form additional pathways to national quality of life.

6. Conclusion

This study distinguishes cognitive and economic resources, health financing, basic infrastructure, and service capacity in a cross-national account of subjective well-being. Cognitive human capital had the largest total association among the three upstream predictors in both models, with indirect components

predominating for happiness and a larger direct component for life satisfaction. Health expenditure had significant positive direct associations with both outcomes, while the infrastructure and capacity results underscored the importance of separating health-related dimensions. These patterns support assessing national well-being through multiple evaluative measures and examining financial allocation alongside the infrastructure and services it is intended to support.

Declarations

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Use of generative AI and AI-assisted technologies in the writing process: During the preparation of this work, the authors used ChatGPT (<https://chat.openai.com/>) in order to improve language and readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Appendix A

Table A1. Descriptive statistics for all single indicators in alphabetic order

Variable	N	M	SD	Mdn.	Min.	Max.
Drinking water access (tot– imp.)	207	90.39	14.61	97.60	35.10	100.00
GDP/c PPP 2000 (k-int. \$)	240	17.79	20.93	9.43	0.70	114.14
GDP/c PPP 2001 (k-int. \$)	240	18.04	21.13	9.57	0.72	116.26
GDP/c PPP 2002 (k-int. \$)	241	18.43	21.32	9.70	0.75	118.76
GDP/c PPP 2003 (k-int. \$)	241	18.87	21.73	9.80	0.78	120.40
GDP/c PPP 2004 (k-int. \$)	241	19.67	22.60	10.24	0.80	123.72
GDP/c PPP 2005 (k-int. \$)	241	20.25	22.97	10.46	0.83	124.87
GDP/c PPP 2006 (k-int. \$)	242	21.35	24.17	11.13	0.86	130.28
GDP/c PPP 2007 (k-int. \$)	243	22.04	24.50	11.87	0.89	138.68
GDP/c PPP 2008 (k-int. \$)	245	22.26	24.09	12.38	0.92	135.81
GDP/c PPP 2009 (k-int. \$)	246	21.51	22.87	12.51	0.96	129.00
GDP/c PPP 2010 (k-int. \$)	246	22.08	23.76	13.05	0.99	131.43
GDP/c PPP 2011 (k-int. \$)	246	22.59	24.65	13.10	0.99	155.39
GDP/c PPP 2012 (k-int. \$)	246	22.76	24.64	13.38	1.00	164.24
GDP/c PPP 2013 (k-int. \$)	247	22.88	24.73	13.80	1.00	174.57
GDP/c PPP 2014 (k-int. \$)	247	23.11	24.41	14.22	1.00	162.81
GDP/c PPP 2015 (k-int. \$)	247	23.26	23.77	14.54	1.00	130.10
GDP/c PPP 2016 (k-int. \$)	247	23.56	23.88	15.02	1.01	133.66
GDP/c PPP 2017 (k-int. \$)	247	24.06	24.29	15.43	1.02	133.32
GDP/c PPP 2018 (k-int. \$)	247	24.52	24.68	16.14	1.05	139.54
GDP/c PPP 2019 (k-int. \$)	247	24.87	24.79	16.37	1.06	133.45
GDP/c PPP 2020 (k-int. \$)	247	23.18	22.94	15.41	1.03	129.87
GDP/c PPP 2021 (k-int. \$)	247	24.62	24.66	16.16	1.04	136.77
GDP/c PPP 2022 (k-int. \$)	247	25.40	25.08	16.91	1.03	133.57
GDP/c PPP 2023 (k-int. \$)	245	25.96	25.47	17.09	1.04	130.05
GDP/c PPP 2024 (k-int. \$)	236	26.30	25.60	18.26	1.05	132.57
Health expenditure (% of total government expenditure)	195	10.84	5.45	10.00	1.10	29.50
Hospital beds per 1,000 people	158	3.00	2.33	2.50	0.20	12.80
Life satisfaction	98	0.00	0.88	–0.02	–1.66	1.76
Physicians per 1,000 people	205	2.07	1.86	1.67	0.02	9.54
PIRLS 2001 (z.std.)	33	0.00	1.02	0.44	–2.86	1.04
PIRLS 2006 (z.std.)	39	0.00	1.01	0.44	–2.83	0.92
PIRLS 2011 (z.std.)	48	0.00	1.01	0.45	–2.54	1.02
PIRLS 2016 (z.std.)	47	0.00	1.01	0.44	–2.91	1.14
PIRLS 2021 (z.std.)	55	0.00	1.01	0.31	–3.60	1.42
PISA Math 2000 (z.std.)	41	0.00	1.00	0.28	–2.78	1.37
PISA Math 2003 (z.std.)	40	0.00	1.00	0.29	–2.43	1.22
PISA Math 2006 (z.std.)	57	0.00	1.00	0.35	–2.67	1.35
PISA Math 2009 (z.std.)	73	0.00	1.00	0.30	–2.12	1.71
PISA Math 2012 (z.std.)	65	0.00	1.00	0.22	–1.94	1.88
PISA Math 2015 (z.std.)	71	0.00	1.00	0.30	–2.50	1.90
PISA Math 2018 (z.std.)	78	0.00	1.00	0.21	–2.43	2.36
PISA Math 2022 (z.std.)	81	0.00	1.01	0.06	–1.75	2.37
PISA Reading 2000 (z.std.)	41	0.00	1.00	0.26	–2.69	1.35
PISA Reading 2003 (z.std.)	40	0.00	1.00	0.27	–2.49	1.49
PISA Reading 2006 (z.std.)	56	0.00	1.00	0.34	–3.02	1.67
PISA Reading 2009 (z.std.)	73	0.00	1.00	0.34	–2.67	1.56
PISA Reading 2012 (z.std.)	65	0.00	1.00	0.33	–1.94	1.57
PISA Reading 2015 (z.std.)	71	0.00	1.00	0.40	–2.33	1.49
PISA Reading 2018 (z.std.)	77	0.00	1.00	0.29	–2.21	1.92

Table A1 (continued)

Variable	N	M	SD	Mdn.	Min.	Max.
PISA Reading 2022 (z.std.)	81	0.00	1.01	0.06	-1.90	1.93
PISA Science 2000 (z.std.)	41	0.00	1.00	0.24	-2.66	1.47
PISA Science 2003 (z.std.)	40	0.00	1.00	0.17	-2.39	1.40
PISA Science 2006 (z.std.)	57	0.00	1.00	0.29	-2.77	1.65
PISA Science 2009 (z.std.)	73	0.00	1.00	0.40	-2.40	1.58
PISA Science 2012 (z.std.)	65	0.00	1.00	0.32	-2.11	1.56
PISA Science 2015 (z.std.)	71	0.00	1.00	0.19	-2.77	1.83
PISA Science 2018 (z.std.)	78	0.00	1.00	0.16	-2.41	2.52
PISA Science 2022 (z.std.)	81	0.00	1.01	0.00	-1.80	2.07
Sanitation facility access	203	87.62	19.62	98.50	17.80	100.00
TIMSS Math 4th grad. 2003 (z.std.)	24	0.00	1.02	0.29	-2.53	1.36
TIMSS Math 4th grad. 2007 (z.std.)	37	0.00	1.01	0.38	-2.71	1.54
TIMSS Math 4th grad. 2011 (z.std.)	52	0.00	1.01	0.26	-3.01	1.59
TIMSS Math 4th grad. 2015 (z.std.)	49	0.00	1.01	0.28	-2.32	1.83
TIMSS Math 4th grad. 2019 (z.std.)	66	-1.06	2.85	0.13	-7.78	1.93
TIMSS Math 4th grad. 2023 (z.std.)	57	0.00	1.02	0.19	-2.54	2.01
TIMSS Math 8th grad. 2003 (z.std.)	46	0.00	1.01	0.21	-2.57	1.88
TIMSS Math 8th grad. 2007 (z.std.)	51	0.00	1.01	0.15	-2.00	2.06
TIMSS Math 8th grad. 2011 (z.std.)	46	0.00	1.01	-0.03	-2.10	2.08
TIMSS Math 8th grad. 2015 (z.std.)	39	0.00	1.01	0.19	-1.68	2.08
TIMSS Math 8th grad. 2019 (z.std.)	66	-3.35	4.13	-1.21	-8.18	2.12
TIMSS Math 8th grad. 2023 (z.std.)	44	0.00	1.01	0.20	-3.07	1.91
TIMSS Science 4th grad. 2003 (z.std.)	24	0.00	1.02	0.49	-2.61	1.03
TIMSS Science 4th grad. 2007 (z.std.)	37	0.00	1.01	0.50	-3.05	1.28
TIMSS Science 4th grad. 2011 (z.std.)	52	0.00	1.01	0.39	-3.24	1.32
TIMSS Science 4th grad. 2015 (z.std.)	47	0.00	1.01	0.36	-2.87	1.49
TIMSS Science 4th grad. 2019 (z.std.)	66	-0.99	2.69	0.19	-7.28	1.55
TIMSS Science 4th grad. 2023 (z.std.)	57	0.00	1.02	0.29	-3.30	1.99
TIMSS Science 8th grad. 2003 (z.std.)	45	0.00	1.01	0.11	-3.08	1.46
TIMSS Science 8th grad. 2007 (z.std.)	51	0.00	1.01	0.03	-2.76	1.73
TIMSS Science 8th grad. 2011 (z.std.)	46	0.00	1.01	0.01	-2.52	1.79
TIMSS Science 8th grad. 2015 (z.std.)	39	0.00	1.01	0.22	-2.17	1.88
TIMSS Science 8th grad. 2019 (z.std.)	66	-3.77	4.63	-0.83	-9.21	2.22
TIMSS Science 8th grad. 2023 (z.std.)	44	0.00	1.01	0.19	-3.99	1.86
World Happiness Report – Ladder score 2011	156	5.39	1.10	5.23	3.01	7.86
World Happiness Report – Ladder score 2012	156	5.42	1.10	5.33	2.94	7.69
World Happiness Report – Ladder score 2014	158	5.38	1.14	5.23	2.84	7.59
World Happiness Report – Ladder score 2015	157	5.38	1.14	5.31	2.91	7.53
World Happiness Report – Ladder score 2016	155	5.35	1.13	5.28	2.69	7.54
World Happiness Report – Ladder score 2017	156	5.38	1.12	5.38	2.91	7.63
World Happiness Report – Ladder score 2018	156	5.41	1.11	5.38	2.85	7.77
World Happiness Report – Ladder score 2019	153	5.47	1.11	5.52	2.57	7.81
World Happiness Report – Ladder score 2020	149	5.53	1.07	5.53	2.52	7.84
World Happiness Report – Ladder score 2021	146	5.55	1.09	5.57	2.40	7.82
World Happiness Report – Ladder score 2022	137	5.54	1.14	5.68	1.86	7.80
World Happiness Report – Ladder score 2023	143	5.53	1.17	5.79	1.72	7.74
World Happiness Report – Ladder score 2024	147	5.58	1.16	5.87	1.36	7.74
World Happiness Report – Ladder score 2025	147	5.65	1.14	5.94	1.45	7.76

Note. Assessment-year labels refer to international study cycles. Table A1 presents descriptive statistics for the individual indicators; Tables 1 and A2 summarize the main analytic variables.

Table A2. Descriptive statistics for main variables in the analytic dataset

Variable	N	M	SD	Mdn.	Min.	Max.
Cognitive human capital ¹	113	0.02	1.08	−0.18	−3.19	2.04
Health expenditure ¹	199	0.00	1.00	−0.12	−1.80	3.39
Access to water and sanitation ¹	205	−0.03	0.98	0.48	−3.34	0.66
Health system capacity ¹	209	−0.06	0.91	−0.25	−1.15	3.51
Wealth ²	201	23.95	24.86	14.25	10.17	128.82
Happiness ³	169	5.43	1.09	5.50	2.84	7.66
Life satisfaction ¹	100	0.00	0.87	0.02	−1.76	1.66

Note. ¹z-standardized; ² in k-International dollars; ³ original score from source.

Table A2 summarizes the main variables on the scales specified in its note. The analytic dataset retains cases with observations on at least two variables. Source-indicator distributions and observation periods are provided in Tables A1 and 1.

Appendix B

Analytical procedure

Analyses were conducted in R using the packages: *psych*, *lavaan*, and *nFactors*. The following steps are outlined in detail below.

World Happiness Report country-level ladder scores were transformed from long to wide format using the year labels in the source dataset.

```
DATA_SWB_WHR_SUB <- DATA_SWB_WHR[, c("Country.name", "ISO", "Year", "SWB_WHR")]
DATA_SWB_WHR_SUB$Year <- as.integer(DATA_SWB_WHR_SUB$Year)
DATA_SWB_WHR_SUB$YearVar <- paste0("SWB_WHR_", DATA_SWB_WHR_SUB$Year)
DATA_SWB_WHR_SUB_WID <- reshape(
  DATA_SWB_WHR_SUB[, c("Country.name", "ISO", "YearVar", "SWB_WHR")],
  idvar = c("Country.name", "ISO"),
  timevar = "YearVar",
  v.names = "SWB_WHR",
  direction = "wide")
```

GDP per capita (PPP) values were harmonized across years, transformed as $\log(\text{GDP per capita (PPP)} + 1)$ using the natural logarithm, and subsequently averaged to obtain a single indicator.

```
DATA_ALL <- merge( DATA_ALL, DATA_ECN[, c("ISO", "ECN_GDP_PPP_000", "ECN_GDP_PPP_001",
"ECN_GDP_PPP_002", "ECN_GDP_PPP_003", "ECN_GDP_PPP_004", "ECN_GDP_PPP_005", "ECN_GDP_PPP_006",
"ECN_GDP_PPP_007", "ECN_GDP_PPP_008", "ECN_GDP_PPP_009", "ECN_GDP_PPP_010", "ECN_GDP_PPP_011",
"ECN_GDP_PPP_012", "ECN_GDP_PPP_013", "ECN_GDP_PPP_014", "ECN_GDP_PPP_015", "ECN_GDP_PPP_016",
"ECN_GDP_PPP_017", "ECN_GDP_PPP_018", "ECN_GDP_PPP_019", "ECN_GDP_PPP_020", "ECN_GDP_PPP_021",
"ECN_GDP_PPP_022", "ECN_GDP_PPP_023", "ECN_GDP_PPP_024")], by = "ISO", all = TRUE, sort = FALSE)
vars <- grep("^ECN_GDP_PPP_", names(DATA_ALL), value = TRUE)
DATA_ALL[paste0(vars, "_LOG")] <- log(DATA_ALL[vars] + 1)
```

The indicators of general cognitive competence (GCC), that is, cognitive human capital, showed very high internal consistency (Cronbach's $\alpha = .96$, standardized $\alpha = .99$), and omega hierarchical suggested the presence of a strong general factor ($\omega_h = .85$). To keep the measurement model manageable, individual achievement scores were combined into six broader composites representing mathematics, science, and reading performance in both PISA and TIMSS/PIRLS. These composites were used as indicators of a latent GCC factor estimated in lavaan with confirmatory factor analysis. Models were fitted using robust maximum likelihood estimation (MLR), and missing values were handled via full-information maximum likelihood (FIML).

```
DATA_ALL$SAS_PIS_MTH <- rowMeans(DATA_ALL[, c("PIS_000_MTH_ZST", "PIS_003_MTH_ZST", "PIS_006_MTH_ZST",
"PIS_009_MTH_ZST", "PIS_012_MTH_ZST", "PIS_015_MTH_ZST", "PIS_018_MTH_ZST", "PIS_022_MTH_ZST")], na.rm =
TRUE)
DATA_ALL$SAS_PIS_SCI <- rowMeans(DATA_ALL[, c("PIS_003_SCI_ZST", "PIS_006_SCI_ZST", "PIS_009_SCI_ZST",
"PIS_012_SCI_ZST", "PIS_015_SCI_ZST", "PIS_018_SCI_ZST", "PIS_022_SCI_ZST")], na.rm = TRUE)
DATA_ALL$SAS_PIS_REA <- rowMeans(DATA_ALL[, c("PIS_000_REA_ZST", "PIS_003_REA_ZST", "PIS_006_REA_ZST",
"PIS_009_REA_ZST", "PIS_012_REA_ZST", "PIS_015_REA_ZST", "PIS_018_REA_ZST", "PIS_022_REA_ZST")], na.rm =
TRUE)
DATA_ALL$SAS_TIP_MTH <- rowMeans(DATA_ALL[, c("TIP_003_MTH_4TH_ZST", "TIP_003_MTH_8TH_ZST",
"TIP_007_MTH_4TH_ZST", "TIP_007_MTH_8TH_ZST", "TIP_011_MTH_4TH_ZST", "TIP_011_MTH_8TH_ZST",
"TIP_015_MTH_4TH_ZST", "TIP_015_MTH_8TH_ZST", "TIP_018_MTH_4TH_ZST", "TIP_018_MTH_8TH_ZST",
"TIP_023_MTH_4TH_ZST", "TIP_023_MTH_8TH_ZST")], na.rm = TRUE)
DATA_ALL$SAS_TIP_SCI <- rowMeans(DATA_ALL[, c("TIP_003_SCI_4TH_ZST", "TIP_003_SCI_8TH_ZST",
"TIP_007_SCI_4TH_ZST", "TIP_007_SCI_8TH_ZST", "TIP_011_SCI_4TH_ZST", "TIP_011_SCI_8TH_ZST",
"TIP_015_SCI_4TH_ZST", "TIP_015_SCI_8TH_ZST", "TIP_018_SCI_4TH_ZST", "TIP_018_SCI_8TH_ZST",
"TIP_023_SCI_4TH_ZST", "TIP_023_SCI_8TH_ZST")], na.rm = TRUE)
DATA_ALL$SAS_TIP_REA <- rowMeans(DATA_ALL[, c("TIP_002_REA_ZST", "TIP_006_REA_ZST", "TIP_011_REA_ZST",
"TIP_016_REA_ZST")], na.rm = TRUE)
MODL_GCC <- 'GCC =~ SAS_PIS_MTH + SAS_PIS_SCI + SAS_PIS_REA + SAS_TIP_MTH + SAS_TIP_SCI + SAS_TIP_REA'
idx <-
!is.na(DATA_ALL$SAS_PIS_MTH) |
!is.na(DATA_ALL$SAS_PIS_SCI) |
!is.na(DATA_ALL$SAS_PIS_REA) |
!is.na(DATA_ALL$SAS_TIP_MTH) |
!is.na(DATA_ALL$SAS_TIP_SCI) |
!is.na(DATA_ALL$SAS_TIP_REA)
DATA_GCC <- DATA_ALL[idx, ]
fit <- cfa(model = MODL_GCC, data = DATA_GCC, std.ov = TRUE, missing = "fiml", estimator = "MLR",
fixed.x = FALSE, check.gradient = TRUE)
```

Health-related indicators were evaluated before constructing composite measures. The initial set included national health expenditures, access to improved drinking water and sanitation, physician density, and hospital bed availability.

```
DATA_HLT <- DATA_ALL[, c("ISO", "HLT_HEP_NBG", "HLT_DWA_IMP_TOT", "HLT_SFA_IMP_TOT", "HLT_PPC",
"HLT_HPC")]
DATA_HLT_REL <- DATA_ALL[, c("HLT_HEP_NBG", "HLT_DWA_IMP_TOT", "HLT_SFA_IMP_TOT", "HLT_PPC", "HLT_HPC")]
alpha(DATA_HLT_REL)
omega(DATA_HLT_REL)
```

Country-level datasets for cognitive competence, health, subjective well-being, life satisfaction, and economic performance were merged using ISO-ALPHA-3 country codes.

Descriptive statistics were calculated using *psych::describe()*. Correlations were estimated from a FIML-based correlation matrix obtained with *lavaan::lavCor()*.

```
vars_raw <- DATA_ANA[, setdiff(names(DATA_ANA), "ISO"), drop = FALSE]; is_num <- sapply(vars_raw,
is.numeric); vars <- vars_raw[, is_num, drop = FALSE]
all_na <- sapply(vars, function(x) all(is.na(x))); too_few_obs <- sapply(vars, function(x) sum(!
is.na(x)) < 2); zero_var <- sapply(vars, function(x) {x_nonmiss <- x[!is.na(x)]; if(length(x_nonmiss) <
2) return(TRUE); v <- var(x_nonmiss); is.na(v) || v == 0})
vars_clean <- vars[, !(all_na | too_few_obs | zero_var), drop = FALSE]
vars_scaled <- as.data.frame(scale(vars_clean))
all_na2 <- sapply(vars_scaled, function(x) all(is.na(x))); too_few_obs2 <- sapply(vars_scaled,
function(x) sum(!is.na(x)) < 2); zero_var2 <- sapply(vars_scaled, function(x) {x_nonmiss <- x[!
is.na(x)]; if(length(x_nonmiss) < 2) return(TRUE); v <- var(x_nonmiss); is.na(v) || v == 0})
vars_final <- vars_scaled[, !(all_na2 | too_few_obs2 | zero_var2), drop = FALSE]
lavCor_result <- tryCatch(lavaan::lavCor(object = vars_final, missing = "fiml", estimator = "ML", output
= "cor"), error = function(e) NULL)
if(!is.null(lavCor_result)) { cor_mat <- as.matrix(lavCor_result) } else { corFiml_result <-
tryCatch(psych::corFiml(vars_final), error = function(e) NULL); if(!is.null(corFiml_result)) { cor_mat
<- as.matrix(corFiml_result) } else { stop("Sowohl lavaan::lavCor() als auch psych::corFiml() sind
fehlgeschlagen.") } }
rownames(cor_mat) <- colnames(vars_final); colnames(cor_mat) <- colnames(vars_final)
```

The primary analyses consisted of two structural path models estimated in *lavaan*. One model predicted happiness, and the other predicted life satisfaction. In both models, GCC, GDP, HEX, ISH, and HSC were specified as direct predictors of the outcome. GCC was additionally modeled as a predictor of GDP and the health-related variables. GDP and health expenditures were assumed to influence health infrastructure and health system capacity, and a residual covariance between ISH and HSC was estimated. Indirect and total effects were calculated to assess whether associations between cognitive competence and well-being could be explained through economic and health-related pathways. Both path models were saturated ($df = 0$).

Code for path model: Subjective well-being

```
MODL_IP1 <- '
SWB ~ c_GCC*GCC + b_ISH*HLT_ISH + b_HSC*HLT_HSC + b_GDP*GDP + c_HEX*HLT_HEX
HLT_ISH ~ a_GCC_ISH*GCC + d_GDP_ISH*GDP + a_HEX_ISH*HLT_HEX
HLT_HSC ~ a_GCC_HSC*GCC + d_GDP_HSC*GDP + a_HEX_HSC*HLT_HEX
HLT_HEX ~ a_GCC_HEX*GCC + d_GDP_HEX*GDP
GDP ~ a_GCC_GDP*GCC
HLT_ISH ~~ HLT_HSC
ind_GCC_ISH := a_GCC_ISH*b_ISH
ind_GCC_HSC := a_GCC_HSC*b_HSC
ind_HEX_ISH := a_HEX_ISH*b_ISH
ind_HEX_HSC := a_HEX_HSC*b_HSC
ind_GCC_HEX_ISH := a_GCC_HEX*a_HEX_ISH*b_ISH
ind_GCC_HEX_HSC := a_GCC_HEX*a_HEX_HSC*b_HSC
ind_GCC_GDP := a_GCC_GDP*b_GDP
ind_GCC_GDP_ISH := a_GCC_GDP*d_GDP_ISH*b_ISH
ind_GCC_GDP_HSC := a_GCC_GDP*d_GDP_HSC*b_HSC
ind_GDP_ISH := d_GDP_ISH*b_ISH
ind_GDP_HSC := d_GDP_HSC*b_HSC
ind_GDP_HEX := d_GDP_HEX*c_HEX
ind_GDP_HEX_ISH := d_GDP_HEX*a_HEX_ISH*b_ISH
ind_GDP_HEX_HSC := d_GDP_HEX*a_HEX_HSC*b_HSC
ind_GCC_HEX := a_GCC_HEX*c_HEX
ind_GCC_GDP_HEX := a_GCC_GDP*d_GDP_HEX*c_HEX
ind_GCC_GDP_HEX_ISH := a_GCC_GDP*d_GDP_HEX*a_HEX_ISH*b_ISH
ind_GCC_GDP_HEX_HSC := a_GCC_GDP*d_GDP_HEX*a_HEX_HSC*b_HSC
```

```

ind_total_GCC := ind_GCC_ISH + ind_GCC_HSC + ind_GCC_GDP + ind_GCC_HEX + ind_GCC_HEX_ISH +
ind_GCC_HEX_HSC + ind_GCC_GDP_ISH + ind_GCC_GDP_HSC + ind_GCC_GDP_HEX + ind_GCC_GDP_HEX_ISH +
ind_GCC_GDP_HEX_HSC
ind_total_GDP := ind_GDP_ISH + ind_GDP_HSC + ind_GDP_HEX + ind_GDP_HEX_ISH + ind_GDP_HEX_HSC
ind_total_HEX := ind_HEX_ISH + ind_HEX_HSC
total_GCC := c_GCC + ind_total_GCC
total_GDP := b_GDP + ind_total_GDP
total_HEX := c_HEX + ind_total_HEX'
fit <- cfa(MODL_IP1, DATA_ANA, std.ov = TRUE, missing = "FIML", estimator = "ML", fixed.x = FALSE,
check.gradient = TRUE)
summary(fit, fit.measures = TRUE, standardized = TRUE, rsquare = TRUE)
standardizedSolution(fit, type = "std.all")
parameterEstimates(fit, standardized = TRUE, ci = TRUE)

```

Code for path model: Life satisfaction

```

MODL_IP1 <- '
STF ~ c_GCC*GCC + b_ISH*HLT_ISH + b_HSC*HLT_HSC + b_GDP*GDP + c_HEX*HLT_HEX
HLT_ISH ~ a_GCC_ISH*GCC + d_GDP_ISH*GDP + a_HEX_ISH*HLT_HEX
HLT_HSC ~ a_GCC_HSC*GCC + d_GDP_HSC*GDP + a_HEX_HSC*HLT_HEX
HLT_HEX ~ a_GCC_HEX*GCC + d_GDP_HEX*GDP
GDP ~ a_GCC_GDP*GCC
HLT_ISH ~~ HLT_HSC
ind_GCC_ISH := a_GCC_ISH*b_ISH
ind_GCC_HSC := a_GCC_HSC*b_HSC
ind_HEX_ISH := a_HEX_ISH*b_ISH
ind_HEX_HSC := a_HEX_HSC*b_HSC
ind_GCC_HEX_ISH := a_GCC_HEX*a_HEX_ISH*b_ISH
ind_GCC_HEX_HSC := a_GCC_HEX*a_HEX_HSC*b_HSC
ind_GCC_GDP := a_GCC_GDP*b_GDP
ind_GCC_GDP_ISH := a_GCC_GDP*d_GDP_ISH*b_ISH
ind_GCC_GDP_HSC := a_GCC_GDP*d_GDP_HSC*b_HSC
ind_GDP_ISH := d_GDP_ISH*b_ISH
ind_GDP_HSC := d_GDP_HSC*b_HSC
ind_GDP_HEX := d_GDP_HEX*c_HEX
ind_GDP_HEX_ISH := d_GDP_HEX*a_HEX_ISH*b_ISH
ind_GDP_HEX_HSC := d_GDP_HEX*a_HEX_HSC*b_HSC
ind_GCC_HEX := a_GCC_HEX*c_HEX
ind_GCC_GDP_HEX := a_GCC_GDP*d_GDP_HEX*c_HEX
ind_GCC_GDP_HEX_ISH := a_GCC_GDP*d_GDP_HEX*a_HEX_ISH*b_ISH
ind_GCC_GDP_HEX_HSC := a_GCC_GDP*d_GDP_HEX*a_HEX_HSC*b_HSC
ind_total_GCC := ind_GCC_ISH + ind_GCC_HSC + ind_GCC_GDP + ind_GCC_HEX + ind_GCC_HEX_ISH +
ind_GCC_HEX_HSC + ind_GCC_GDP_ISH + ind_GCC_GDP_HSC + ind_GCC_GDP_HEX + ind_GCC_GDP_HEX_ISH +
ind_GCC_GDP_HEX_HSC
ind_total_GDP := ind_GDP_ISH + ind_GDP_HSC + ind_GDP_HEX + ind_GDP_HEX_ISH + ind_GDP_HEX_HSC
ind_total_HEX := ind_HEX_ISH + ind_HEX_HSC
total_GCC := c_GCC + ind_total_GCC
total_GDP := b_GDP + ind_total_GDP
total_HEX := c_HEX + ind_total_HEX'
fit <- cfa(MODL_IP1, DATA_ANA, std.ov = TRUE, missing = "FIML", estimator = "ML", fixed.x = FALSE,
check.gradient = TRUE)
summary(fit, fit.measures = TRUE, standardized = TRUE, rsquare = TRUE)
standardizedSolution(fit, type = "std.all")
parameterEstimates(fit, standardized = TRUE, ci = TRUE)

```

Appendix C

Table C1 reports correlations estimated from the covariance matrix using FIML. All listed correlations were statistically significant ($p < .001$). Cognitive human capital correlated positively with access to water and sanitation ($r = .60$), health system capacity ($r = .73$), wealth ($r = .67$), happiness ($r = .68$), and life satisfaction ($r = .61$). Wealth correlated .76 with happiness and .50 with life satisfaction. The two well-being indicators correlated .70. The correlations highlighted in this paragraph meet the conventional .50 benchmark for a large association (Cohen, 1988). Marginal associations differ from the conditional coefficients in the path models.

Table C1. FIML-estimated correlation matrix for the main variables

Variable	<i>N</i> *	CogAb	HeaExp	Access to w/s	HeaSysCap	Wealth	Hap	LifSat
Cognitive ability (CogAb)	113	1	.59	.60	.73	.67	.68	.61
Health expenditure (HeaExp)	199	<.001	1	.53	.50	.51	.67	.70
Access to water/sanitation (Access to w/s)	205	<.001	<.001	1	.57	.51	.67	.32
Health system capacity (HeaSysCap)	209	<.001	<.001	<.001	1	.58	.60	.49
Wealth ^a	201	<.001	<.001	<.001	<.001	1	.76	.50
Happiness (Hap)	169	<.001	<.001	<.001	<.001	<.001	1	.70
Life satisfaction (LifSat)	100	<.001	<.001	<.001	<.001	<.001	<.001	1

Note. Correlations in the upper triangle were estimated from the covariance matrix by FIML using the analytic dataset of 218 countries/political entities. The lower triangle gives the corresponding p values; all listed correlations have $p < .001$. *N** gives the observed country count for each variable, not the pairwise sample size for every correlation.

^aWealth is based on log-transformed GDP per capita (PPP); the exact transformation is defined in Methods.

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