PNAS RESEARCH ARTICLE | SUSTAINABILITY SCIENCE OPEN ACCESS

The global human day

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Edited by B. Turner, Arizona State University, Tempe, AZ; received November 21, 2022; accepted April 18, 2023

The daily activities of ≈8 billion people occupy exactly 24 h per day, placing a strict physical limit on what changes can be achieved in the world. These activities form the basis of human behavior, and because of the global integration of societies and economies, many of these activities interact across national borders. Yet, there is no comprehensive overview of how the finite resource of time is allocated at the global scale. Here, we estimate how all humans spend their time using a generalized, physical outcome–based categorization that facilitates the integration of data from hundreds of diverse datasets. Our compilation shows that most waking hours are spent on activities intended to achieve direct outcomes for human minds and bodies (9.4 h/d), while 3.4 h/d are spent modifying our inhabited environments and the world beyond. The remaining 2.1 h/d are devoted to organizing social processes and transportation. We distinguish activities that vary strongly with GDP per capita, including the time allocated to food provision and infrastructure, vs. those that do not vary consistently, such as meals and transportation time. Globally, the time spent directly extracting materials and energy from the Earth system is small, on the order of 5 min per average human day, while the time directly dealing with waste is on the order of 1 min per day, suggesting a large potential scope to modify the allocation of time to these activities. Our results provide a baseline quantification of the temporal composition of global human life that can be expanded and applied to multiple fields of research.

time use | sustainability | global | sociology | economics

At present, we lack a coherent global understanding of human activities. This is not to say that the study of human activities has been overlooked. On the contrary, activities comprise the core of our species' behavior, and for decades they have been documented by diverse fields including economics (1–3), sociology (4, 5), history (6, 7), and anthropology (8–10). However, economists have focused primarily on paid work activities, relegating other activities to leisure or unpaid work, while sociologists, historians, and anthropologists have often focused their attention on the activities that take place outside the formal economy. Because of deep methodological differences, these studies are very rarely combined, and they have not been previously integrated at the global scale.

A coherent interdisciplinary understanding of activities is important at present because, although the motivations for people to act are couched within the contexts of their own lives, activities are coordinated through economic and societal links to generate a globally integrated human system (11). The food we consume, the clothes we wear, and the material objects we use are largely produced by others in distant parts of the world. Similarly, threats to planetary boundaries, like climate change and biodiversity loss, are the collective outcomes of human activities across the planet (12, 13). Although the consequences of any human undertaking vary greatly with the available technology and other contextual features, the time spent on tasks is a key factor in determining outcomes, whether producing food, constructing buildings, or tackling environmental problems (14, 15). Because global outcomes emerge from the sum of individual actions, it is crucial to understand how global activities influence local changes and vice versa.

Compounding the disciplinary divisions is a geographic fragmentation of activity data. The collection and analysis of activity data have tended to be carried out at the national scale, tailored to the specific needs and objectives of individual countries, and most analyses have focused on wealthy populations. Although there have been some efforts to compare sociological time use data for adults across countries (16–20), they have not previously been used to characterize the global human system in a broader sense. Economic activities are more often captured in global databases (21), yet where global economic analyses have been carried out, they have typically focused on individual sectors of the economy, or relied heavily on monetary valuations to combine activities among countries. Because wages and capital valuations can vary dramatically between countries, a monetary perspective does not provide a clear picture of the ends to which humanity's global supply of labor is directed.

Significance

Understanding how the global human system functions is crucial if we are to sustainably navigate planetary boundaries, adapt to rapid technological change such as artificial intelligence, and achieve global development goals. But, the vast scope and diversity of human endeavors presents a major challenge for holistic assessment. Here, we address this problem by providing a global estimate of time use by all humans, integrating economic and noneconomic data within a consistent framework. Our findings provide a bird's eye perspective on what our species does, including how economic activities fit into the backdrop of life, and reveal activities for which there is significant potential for change.

Author contributions: W.F. and E.D.G. designed research; W.F., E.D.G., J.C., E.F., P.L.M., K.M., V.X., X.W., and S.X. performed research; W.F., E.D.G., C.B.-L., I.H., and R.M. analyzed data; and W.F., and E.D.G. wrote the paper.

The authors declare no competing interest.

This article is a PNAS Direct Submission.

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This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2219564120/-/DCSupplemental.

Published June 12, 2023.

Table 1. Categories used to harmonize data, according to the Motivating-Outcome-Oriented General Activity Lexicon (MOOGAL)

Group	Category	Description
External outcomes	Food provision	Providing food to humans, including agriculture and fishing, the processing of food items, cooking, serving, and cleanup
	Nonfood provision	Providing raw materials and energy to the technosphere, including mining, lumber, fossil fuels, and renewable energy
	Technosphere modification	The construction and maintenance of buildings, infrastructure, and movable artifacts
	Maintenance of surroundings	Cleaning surfaces and arranging the spaces that humans inhabit, taking care of accompanying plants and animals, disposing of wastes
Direct human outcomes	Somatic maintenance	Caring for the cleanliness, appearance, and health of human bodies, including medical care and childcare
	Deliberate neural restructuring	Education, both formal and informal, research in the academic and private sector, and religious activities
	Experience oriented	Engaging in activities to provide desired experiences, including through use of media, interactive hobbies and sports, socializing, and meals
Organizational outcomes	Organization	Activities that do not directly support any of the above outcomes, but instead serve to change the locations of entities, or allocate the time and access rights of humans, including through commerce, finance, real estate, law, and governance

In contrast to monetary metrics, which are not strictly physical, all humans exist for exactly 24 h per day and spend each minute doing something (22, 23). This 24-h time budget constraint is applicable at any scale, as well as over the history of human development. A complete and holistic quantification of how global humanity allocates its ~190 billion hours per day could therefore provide a firm grounding from which to assess how human behavior is changing over time, as well as the scope and plausibility of strategies to simultaneously achieve multiple goals, such as the 17 internationally agreed upon Sustainable Development Goals (SDGs) (24, 25). For example, time provides a simple basis for assessing the overall feasibility of reallocating labor to constructing nonfossil fuel energy systems (advancing SDGs 7 and 9) or dealing with plastic pollution (SDGs 12, 14, and 15) while maintaining meaningful employment in a globalized economy (SDGs 8 and 9). It also represents an important, human-centered perspective on development and the evolution of human experience in the face of social and technological shifts, including the accelerated transformation of labor markets through urbanization, automation, and artificial intelligence (26–28).

Making use of the 24-h constraint requires a holistic assessment of activities. The disciplinary division between paid and unpaid activities can be resolved by combining observations from economic and sociological time use data with a harmonized set of activity categories. Given that global economic networks exchange vast quantities of materials and goods across national borders, understanding how the time budget constraint relates to physical outcomes also requires assessing activities for the complete population of the world. Combining national data requires taking into account discrepancies in the subsets of the populations surveyed (e.g., labor force and legal adults), as well as addressing numerous variations in reporting conventions and activity categorizations. These methodological hurdles have impeded the development of a unified global perspective on activities.

A Holistic Estimate of Global Time Use

Here, we assemble a complete estimate of what humans are doing, averaged over time and across the entire population, to provide an aggregated high-level view that we refer to as the global human day. We combined available data collected by national statistics agencies, international organizations, and researchers from over 140 countries, wherever available during the period 2000 to 2019 to avoid the economic and social disruption of the COVID-19 pandemic (*SI Appendix*, Tables S1 and S2). We interpolated within geographical regions to countries with incomplete or missing data in order to account for undersampled populations. We assessed the full human lifespan by weighting population-specific time use estimates using age-structured demographic data (*Methods*).

Our approach is enabled by a generalized categorization of activities (29), the Motivating-Outcome-Oriented Generalized Activity Lexicon (MOOGAL), which allows for the integration of data originally collected for diverse sociological, economic, and anthropological purposes. The lexicon is comprised of eight categories (Table 1), which are subdivided into 24 subcategories (Table 2). The subcategories are described in physical, rather than colloquial, terms to limit ambiguity in their application across cultures. Since the MOOGAL lexicon is designed to combine economic and noneconomic data, it differentiates based on the motivating outcome that causes the activity to be undertaken, rather than whether or not the activity is undertaken for pay. For example, both paid daycare work and unpaid care of young children by parents are classified under physical childcare, while food preparation includes both cooking at home and working at a restaurant. Similarly, the time invested by humans as both bus passengers and bus drivers would be included together within human transportation, since changing the locations of humans is the intended outcome for both activities. We produced concordance matrices for crossmapping all time use survey and economic activities to the MOOGAL subcategories, resulting in 3,956 MOOGAL subcategory definitions. Although it is not common to report uncertainty estimates for time use data, we endeavored to provide a partial estimate of the uncertainty range for each global average value. This uncertainty range aims to represent uncertainty in the initial data, the association to MOOGAL subcategories, and from interpolation to countries with missing data, and should be seen as approximate (see *SI Appendix* for a detailed description of the full method).

Table 2. Subcategories of the MOOGAL

Category	Subcategory	Definition	Examples
Food provision	Food growth & collection	All activities related to the growth of edible organic matter, its collection, and initial storage	Crop and animal production. Fishing, hunting, and trapping. Ploughing, clearing of land, sowing, planting, transplanting. Kitchen gardening. Collecting, storing, and stocking of products. Fish farming. Gathering wild products
	Food processing	Transformation of food to prevent spoilage and detoxification, or to create storable beverage and food products	Food manufacturing. Milling, husking, pounding. Beverage manufacturing. Food processing and preservation. Jarring and canning
	Food preparation	Transformation within days or hours of eating. Includes cleanup of preparatory surfaces, serving, and washing of dishes	Cooking. Preparing meals for the home. Washing dishes. Catering. Food and beverage preparation and serving. Parboiling. Bread baking. Serving meals/snacks. Clearing table
Nonfood provision	Materials	The extraction of substances from the Earth system to be used for artifacts, buildings, and infrastructure	Mining and quarrying. Digging out clay, gravel, and sand. Mining of metal ores. Forestry and logging. Nonferrous metal mining. Stone cutting
	Energy	Extraction and provision of energy	Oil and gas extraction. Electric power generation, transmission, and distribution. Gas production and supply industry. Petroleum processing. Mining of uranium and thorium ores. Gathering firewood and other natural products used as fuel
Technosphere modification	Buildings	Construction and maintenance of residential, commercial, and industrial buildings	Home maintenance. DIY home improvement. Construction work. Building and extension of dwelling. Construction activities for own home
	Infrastructure	Construction and maintenance of structures to facilitate the transport of people, materials, and information	Civil engineering. Telecommunications. Construction of roads, railways, and bridges
	Artifacts	Creation and maintenance of movable objects	Manufacturing of base goods. Manufacturing of textiles. Manufacturing of pharmaceuticals. Manufacturing of computer, electronic, and optical products. Making handicrafts, pottery, printing, and other crafts. Assembling machines, equipment, and other products. Vehicle maintenance and repairs. Production of goods for own household use
Maintenance of surroundings	Inhabited environment	Maintaining the cleanliness and order of inhabited spaces and materials, including home, workspace interiors, and grounds	Laundry. Indoor cleaning. Washing clothes and shoes. Ironing. Cleaning dwelling. Care of house plants. Ground maintenance. Pet care. Care of textiles
	Waste management	Dealing with waste and unintended by-products outside of inhabited buildings and their immediate environment	Waste management and remediation services. Sewerage. Recycling. Sewage and refuse disposal, sanitation, and similar activities. Waste disposal. Removing trash
Somatic maintenance	Hygiene & grooming	Maintaining the cleanliness and appearance of the body	Washing yourself, getting dressed. Bathing. Personal care. Grooming. Private activities. Personal hygiene
	Physical childcare	Physical and practical care of young people, including cleaning, feeding, and minding young children to ensure safety	Physical care of children: washing, dressing, and feeding. Supervising children needing care. Minding children. Physical care of preschool children
	Health care	Medical care and physical support to persons in need	Medical care for family members. Health care to oneself. Medical examination or treatment. Physical care of sick or disabled adult. Receiving medical/personal care from professionals. Mental health

Table 2. (Continued)

Category	Subcategory	Definition	Examples
	Sleep & bedrest	Time spent in bed and/or sleeping	Sleeping, naps, sick in bed. Incidental sleeps and naps. Bedridden due to disease
Deliberate neural restructuring	Schooling & research	Deliberate education and research activities	Education. Attending class. Homework and research. Studying and learning. Remote education learning activities. School, technikon, college, university attendance
	Religious practice	Religious practice and ceremonial, social, or cultural events	Ritual ceremonies. Praying. Religious activities. Private prayer, meditation, and other spiritual activities
Organization	Material transportation	Transport undertaken to move artifacts, raw materials, and food	Road freight transport. Shipping. Loading, unloading, handling, and other transportation services. Postal service, couriers, and messengers. Warehousing industry. Transporting in vehicles. Fetching of water
	Human transportation	Transport of persons for the purpose of changing their location	Travel to/from work. Travel for social and cultural activities. Travel to or from school. Commuting, job, and study-related travel. Public transport. Transport of passenger by motorized and nonmotorized transports. Journeying
	Allocation	Activities that are not directly motivated by a specific outcome for humans or the external world, but instead contribute to determining the allocation of time and access rights to humans	Wholesale and commission trade. Retail. Banking. Financial and insurance industry. Public administration and defense. Local government services. Extraterritorial organizations and bodies. Accessing government services. Real estate industry. Legal and accounting activities. Petty trading, street and door-to-door vending, hawking. Grocery shopping. Purchasing goods. Shop online stores. Paying household bills. Household management. Job search
Experience oriented	Meals	Activities centred on eating and drinking, including associated socializing	Eating and drinking. Eating meals/snacks. Pubs and restaurants. Coffee, refreshments. Meals associated with work. Visit to restaurant, café, bar
	Active recreation	Recreation that involves an elevated metabolic activity, whether purely for the experience or including a fitness motivation	Active sports. Ball games. Walks. Wushu and Qigong. Hiking. Walks in forest and on land. Walking the dog. Water sports
	Passive, interactive, and social	Activities undertaken for the purpose of producing a desired experience, including passive observation of media or surroundings, interactive engagement with devices or other people, and socializing	Watching TV. Listening to radio, personal media device, or other audio. Reading. Using computer to read and watch/listen to programs. Doing nothing, rest, and relaxation. Arts and hobbies. Computer games. Visual, literal, and performing arts. Museum/exhibition. Spectator to sports, exhibitions, concerts. Socializing. Attending or hosting social events. Telephone calls. Discussing, gossiping. Family and socializing. Visiting relatives and friends

The Global Human Day. Our resulting estimate of the global human day is shown in Fig. 1, reported as the number of hours per day engaged in each activity, averaged across all humans, where the area of each colored cell is proportional to the amount of time. Sleep and bedrest, the largest category (9.1 ± 0.4 h), is shown as the adjacent crescent. This sleep estimate is significantly larger than the global average of 7.5 h of sleep per day recorded among adults by wearable devices (30), a difference we attribute to the inclusion of children in our estimate and to the time spent in bed but not sleeping (*Methods*).

For the ≈15 h per day of human life not devoted to sleeping and bedrest, the activity subcategories can be summarized according to three large groups. Direct human outcomes (9.4 h), comprising the largest group, are motivated by the immediate consequences they have on humans. These activities include taking care of the appearance, cleanliness and health of human bodies, the deliberate restructuring of human neural pathways, and the generation of desired experiences. The most time-consuming subcategory is passive, interactive, and social activity which includes reading, watching screens, playing games, going for walks, socializing, and sitting doing nothing, and occupies an average of 4.6 ± 0.3 h or ≈31% of the average waking day. The second large group includes activities motivated by external outcomes (3.4 h), i.e., intended to produce physical changes in the world outside humans themselves. These changes

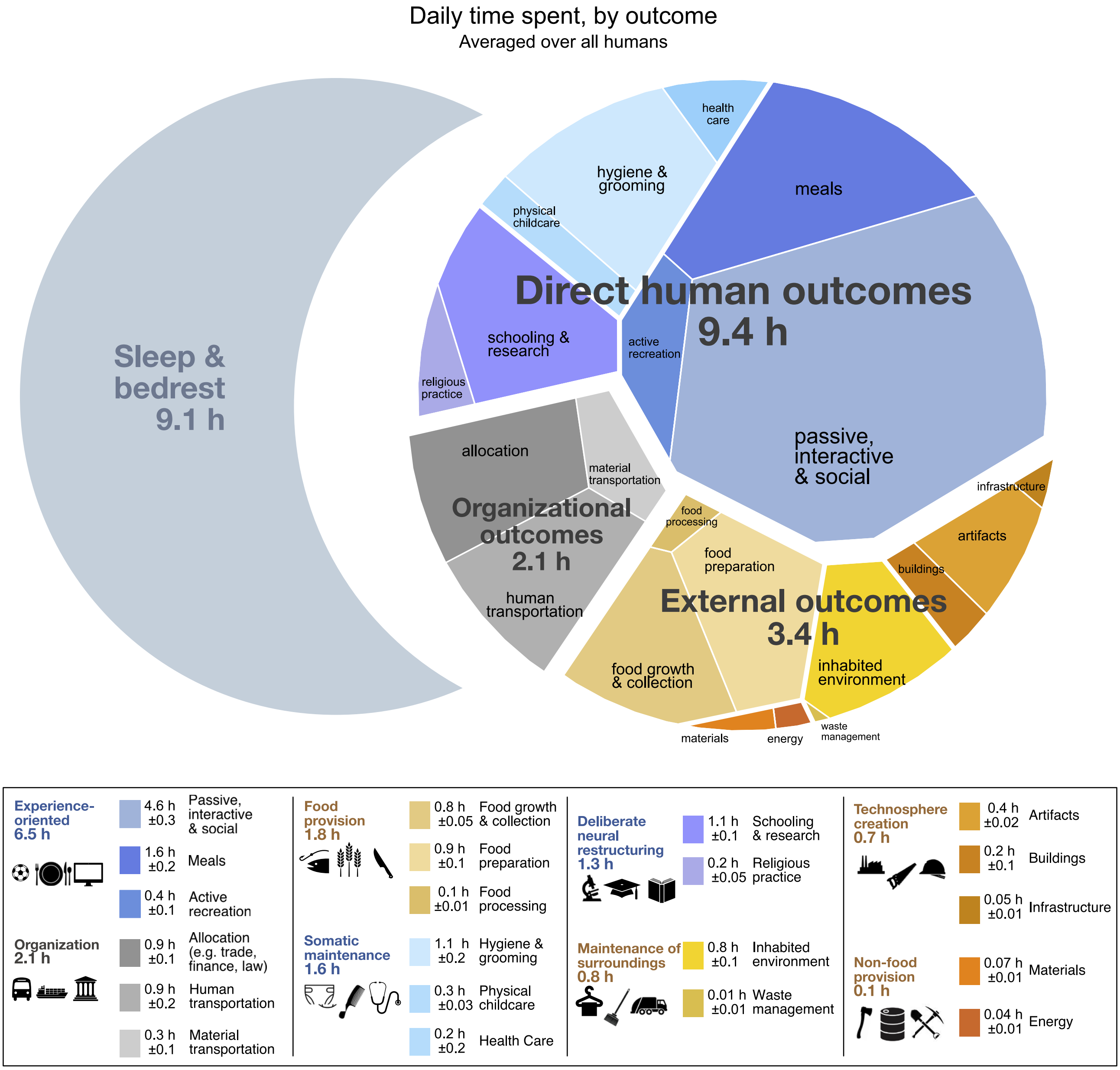

Fig. 1. The global human day, including both work and nonwork activities. The time devoted to each activity, averaged across the entire human population of ≈8 billion people, is indicated by the area of each colored shape in the Voronoi diagram. Direct human outcome activities aim to modify the bodies, neural structures, and experiences of humans. Activities with external outcomes are intended to modify the immediate surroundings of humans, including construction and maintenance of the technosphere, and the provision of food, energy, and materials from the Earth system. Activities with organizational outcomes include moving humans and cargo, as well as activities that allocate labor and access rights such as trade, finance, law, and governance. The time spent in each subcategory is listed below the diagram, in hours per day, with approximate confidence intervals that reflect contributions from the original data sources, interlexicon associations, and interpolation.

include extracting materials and energy from the natural environment, producing food, creating and maintaining movable objects and immovable constructions, and maintaining the cleanliness and tidiness of the spaces humans inhabit. Activities in the third large group are motivated by organizational outcomes (2.1 h), including activities that modify the locations of humans and materials, and an array of activities that are not directly motivated by particular physical outcomes, but instead serve to allocate the time use and access rights of humans (29). Allocation is achieved by mechanisms that vary between cultures and economic systems, including legal and political systems, finance, policing, and shopping.

Time Devoted to the Global Economy. Because our analysis includes both economic and noneconomic data at the global scale, it enables a unique perspective on how economic activities fit into the overall distribution of human activities. Economic activities are defined here as those within the scope of what the International Labor Organization considers "employment," including work for pay or profit as well as the production of nonmarket goods within households. These economic activities account for ≈2.6 h (158 min), roughly 11% of the global human day, or one-sixth of waking hours over the average lifetime. Although this may appear small, it is equivalent to a 41-h work week among the global labor force (which is approximately 66% of the working-age population, those aged 15 to 64 y).

When the global economic activity is viewed on its own (Fig. 2), we see that almost one-third involves the growth and collection of food (44 ± 3 min), mainly in the form of agriculture. Roughly one quarter of economic activity is dedicated to allocation (37 ± 2 min), which includes retail, wholesale, real estate, insurance, finance, law,

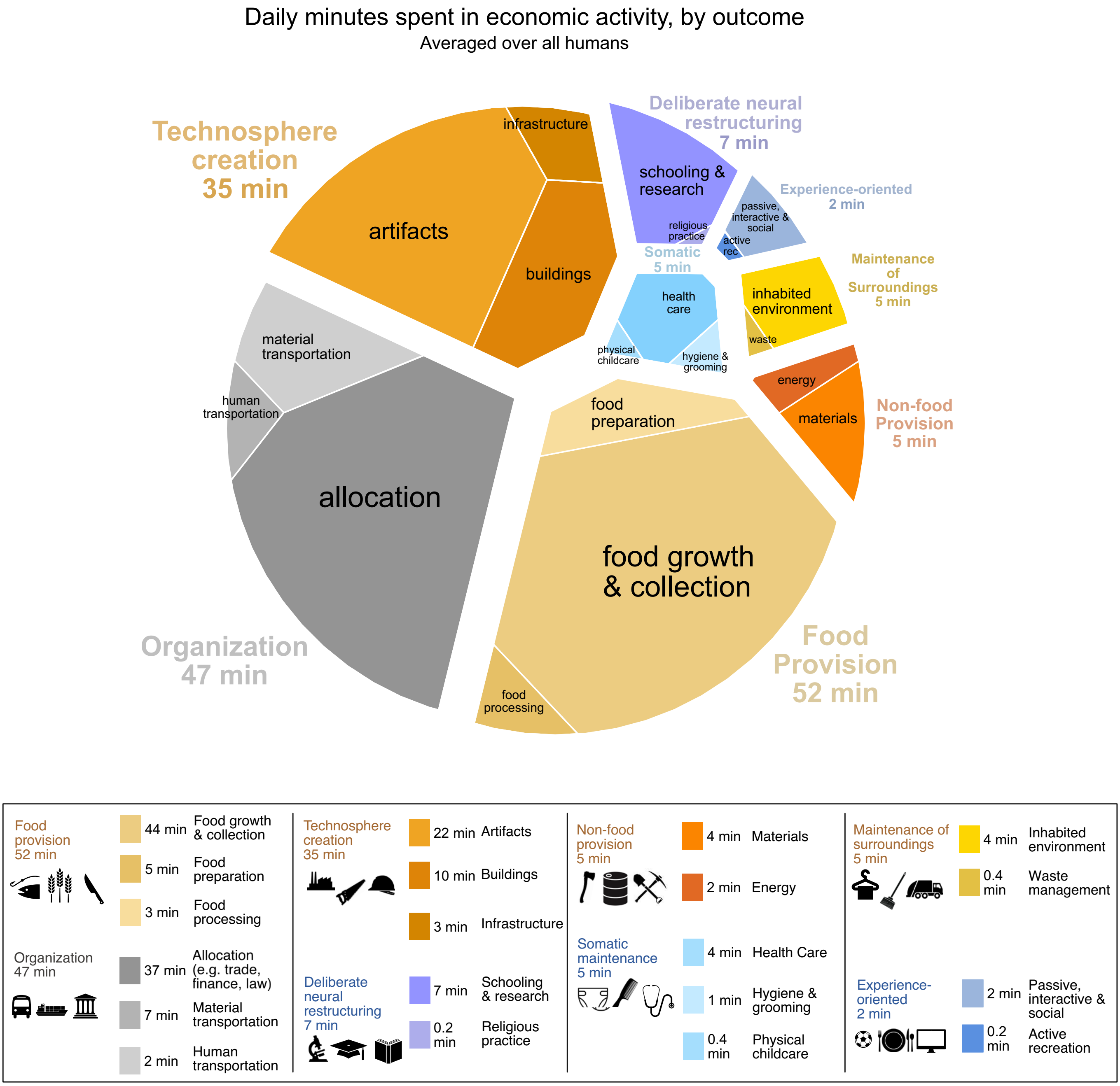

Fig. 2. The global economic day. Voronoi tree is calculated as in Fig. 1, for the average time spent in paid employment and unpaid or other own-use/household production of goods, averaged across the global population. Average times per subcategory are shown at the bottom of the figure, in minutes per day. The sum of all economic activities is ≈2.6 h per day, equivalent to a 41-h work week among ≈66% of the working-age population.

and governance. The production of artifacts, which includes the manufacture of vehicles, machinery, electronics, domestic appliances, and all other movable goods as well as their intermediate components, accounts for roughly one-seventh of the total economic activity (22 ± 2 min). The remaining economic time is mostly partitioned among the construction and maintenance of buildings, freight and other material transportation, food preparation, and schooling and research.

Variation with Material Wealth. Because our data compilation includes formal, informal, subsistence, domestic and care work, as well as nonwork activities, normalized to total populations, it allows a comprehensive comparison of how activities vary between countries. To provide an overview, we show how activities vary in relation to material wealth, for which we use GDP per capita ($US PPP) as a proxy. Our data reveal particularly notable trends in four activities vs. GDP per capita, shown in Fig. 3. The time spent growing and collecting food is large in low-income countries (>1.0 h) but becomes very small in high-income countries (<5 min). This striking trend can be largely attributed to labor-saving technologies (27) that allow the same amount of food to be produced with an order of magnitude less time. The decrease of approximately 1.2 h in food growth and collection over the income range is roughly counterbalanced, perhaps unsurprisingly, by an increase in the time spent engaged in experience-oriented activities (passive, interactive, and social interactions plus meals and active recreation, a ~1.5 h increase). There are also significant increases of the time spent in allocation activities (~0.4 h) and on infrastructure construction and maintenance (~0.1 h) across the range of GDP per capita.

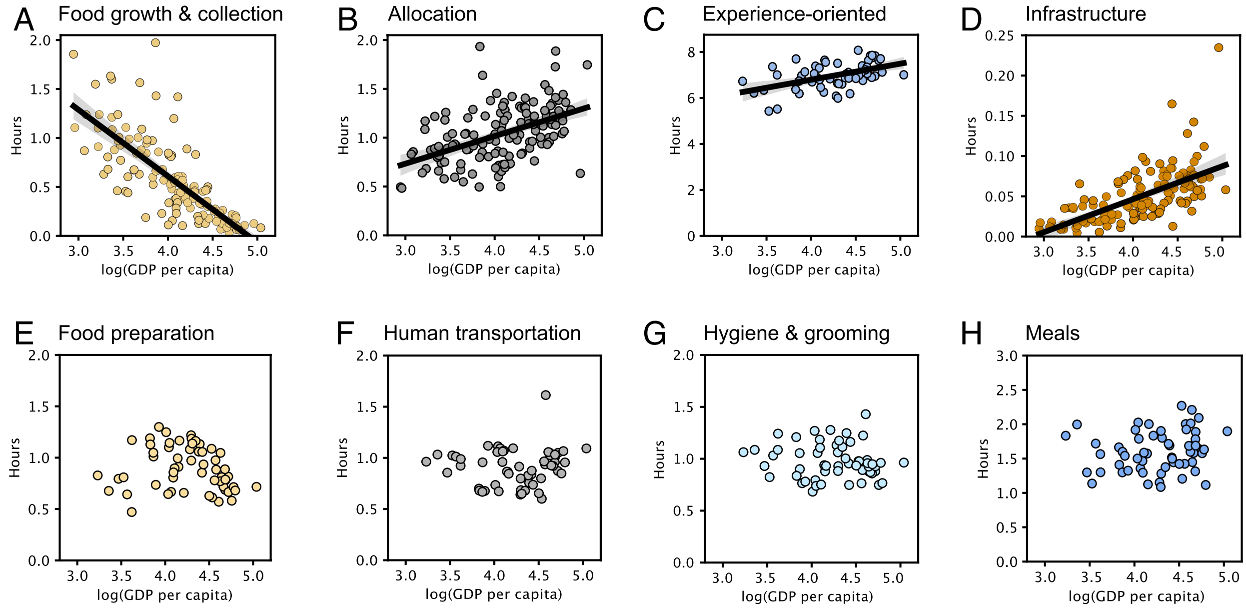

Fig. 3. Activities vs. GDP per capita at the country scale. Each circle represents the population-average time per day for one country. Panels *A*–*D* show subcategories with highly significant linear trends, while panels *E*–*H* do not show significant trends. Panels *A*, *B*, and *D* include only countries with economic data, while other panels include only countries with time use survey data.

In contrast, other activities are remarkably invariant vs. GDP per capita. Food preparation (0.9 ± 0.1 h), human transportation (0.9 ± 0.2 h), hygiene and grooming (1.1 ± 0.2 h), and meals (1.6 ± 0.2) show no detectable trends with GDP per capita (Fig. 3 *E*–*H*). This invariance does not imply that the portions of time devoted to these activities are universal across humans, as they certainly vary among individuals. Rather, our results do not show a consistent variation with GDP at the population level, suggesting that material wealth does not play a large role in determining the allocation of time to these activities. Together, these wealth-invariant activities comprise 4.5 ± 0.4 h or 30% of the waking day.

The relatively constant time spent in human transportation is particularly notable, given that travel is often thought of as a cost that might be alleviated with technology (31), analogous to the large effect of labor-saving technology on agriculture (27). Instead, our data imply that material wealth has a negligible effect on travel time at the population level (Fig. 3*F*). This supports long-standing speculation regarding an inherent travel time budget (32–34), which was originally based on more geographically limited data, and is consistent with the hypothesis that the built environment and transportation technology tend to coevolve to maintain a psychologically bounded average daily travel time (35, 36). This general observation has implications for the potential to reduce transport-related energy expenditure: If travel time is relatively invariant at the population scale, per capita energy consumption can only be reduced by decreasing the energy consumption per travel time. It follows that the energy cost per travel time is the key variable of interest, and that—on their own—reductions of the average energy cost per distance traveled are unlikely to reduce overall energy consumption in daily personal transport.

Time for Sustainable Action. Our analysis shows that the activities through which humans directly modify the state of our planet account for a relatively small portion of the global human day. For example, the extraction of all raw materials such as wood, minerals, and rock requires only 4 ± 1 min, while energy provision, including the extraction and refining of all fossil fuels, is achieved with 2 ± 1 min. This is not to say that these activities are minor in aggregate physical or economic terms: When summed over the global population, ≈780 million person-hours are dedicated to material extraction and energy provision daily, equivalent to ≈285 billion person-hours per year. On their own, these large sums might give the impression that material extraction and energy provision comprise a major component of human activity. But instead, when viewed as a relative fraction of the whole, they are found to be remarkably small compared to activities such as hygiene and grooming, which consume ≈3.2 trillion person-hours per year, roughly 12-fold more.

The concept of Energy Return On Investment (EROI) offers an interesting perspective on the human time invested in energy provision (37). An EROI ratio compares one form of usable energy with the energy investment required to provide it. Our results allow a unique assessment of the average return on human metabolic energy investment. Although the usable energy could be quantified at multiple points, for the sake of argument, we choose the final global energy supply, approximately 13 TW in 2019 (38), to compare with the human metabolic energy expenditure used in the activity of providing that energy supply. If we assume a typical adult human mass of 70 kg, with a basal rate of 1.1 W kg^{-1}, working at a typical rate of 2.5-fold the basal rate (39), our results imply that the average global rate of human metabolic energy invested in all forms of energy provision (2 min per day) is ~2 GW. This is equivalent to an EROI ratio for the human to final energy supply of more than 5,000-fold. This EROI ratio is a factor of 5 to 10 lower than values estimated previously for Italy and the United States by ref. 40, which we attribute to a combination of international exchange and the inclusion of low-efficiency energy forms such as firewood collection in our global estimate. We emphasize that this is a crude estimate, but it shows the extremely high average EROI, relative to metabolic energy, achieved by the global human system.

Because the global supply of energy and materials is currently provided with a small fraction of the total time (amounting to ≈ 3% of the global economic time), the time allocated to these activities could be altered to a relatively large degree without necessarily having a large impact on the time allocated to other activities. This assessment suggests that climate change solutions, such as shifting labor away from fossil fuel industries and into the construction of global renewable power infrastructure, are highly feasible in terms of the global time budget, in that there exists a clear physical scope for humans to reallocate time among the relevant activities without significantly disrupting the overall distribution of time at the population level. The potential of labor-saving technologies to reduce the time required for food growth and collection, highlighted above, suggests that a synergy might exist between the mechanization and electrification of agriculture in low-income countries (41) and the construction of solar energy infrastructure. This does not speak to the policy and economic measures required to engineer such transitions, which are likely to be highly challenging. But, it does indicate that a future with quite different infrastructure and energy flows can be physically achieved without requiring a great disruption in the overall composition of human activities.

Meanwhile, the amount of time devoted to dealing with waste, outside of our dwellings and their immediate surroundings, appears to be very small (≈1 min). We caution that our assessment of waste management time may have been unable to capture time investment by some government agencies, consultants, and the informal economy, so the ~1 min per day may be an underestimate. Nonetheless, this small time investment stands in stark contrast to the time spent cleaning and arranging within our dwellings (≈40 min). It seems plausible that many waste problems, including the accumulation of ocean plastics and water contamination by toxins, could potentially be greatly alleviated through a relatively small reallocation of the total human time budget. Motivating such shifts of time allocation requires dedicated policy and economic strategies, but our analysis suggests that the time is available for the global human system to address 21st-century sustainability goals.

Outlook. The holistic approach to time use presented here can serve as a foundation for future work. Additional dimensions of global time use, beyond the physical outcomes focused upon here, can be resolved through the global application of complementary standardized lexicons (29). These additional dimensions might include social interactions, physical context, or technology use. The geographic distribution of activities can be directly linked to material, energetic, and monetary flows, as well as to subjective experiences, to enhance process understanding. Changes over time in the global human day, informed both by historical records and ongoing monitoring, can potentially provide further insight on long-term behavioral mechanisms and the roles that changes in time allocation play in societal transitions. Globally standardized time use patterns can be applied as human-focused alternatives to GDP (42), and calculations of potential changes in time use may help to chart pathways toward SDGs, applicable for planetary-scale governance (43). Time, it has been said, is the coin of life—and in a globally connected society, it is essential to have a thorough global understanding of how that coin is spent.

Methods

Our estimate of the global human day is constructed as part of the Human Chronome Project (https://humanchronome.org/), based on three primary components, namely nationally representative time use surveys, national statistics of employment and working time according to economic activity, and a multicomponent time use model for youth aged 0 to 17 y. We also include sleep data from wearable devices for comparison with time use survey data. The data sources are briefly described below, followed by the strategy used to interrelate activities through a common lexicon, and a brief discussion of uncertainty. A more thorough description of the method is provided in *SI Appendix*, including supplementary figures and tables.

Time Use Surveys. To provide a baseline for average daily time use, we obtained nationally representative time use surveys from 58 countries comprising approximately 60% of the world population. These surveys are conducted by national statistical agencies with the goal of providing a broad understanding of how the population allocates their time to a set of activities. Most of these surveys report any formal economic participation as a single activity, e.g., "work for employment" (with some exceptions). Survey data are collected via self-completed time diaries, telephone or in-person interviews, online questionnaires, or a combination of these methods. The measure we use is the population-weighted average daily time spent on each activity among all respondents, which is the product of the participant time (the average time spent on each activity only among those who engaged in the activity) and the participation rate (the percentage of all respondents engaging in the activity). When available, the aggregate survey data were downloaded from the respective national statistical agency database, and translated as necessary. If the aggregated datafile could not be located, the relevant table from the survey report was manually transcribed to a computer-readable format. The full list of countries, including the source location, is given in *SI Appendix*, Table S1.

The quality of each survey is assessed according to several key characteristics, notably survey duration, data collection method, and lexicon length. Three quality levels (A, B, and C) are associated with a 5, 10, and 20% baseline uncertainty on the time values reported in the survey, respectively. For details regarding the quality assessment, see *SI Appendix*, section 6.

Economic Activity. The main source for economic data was ILOSTAT, the online repository of labor statistics managed by the International Labour Organization (ILO) Department of Statistics. Mean annual employment and mean weekly working time data, recorded under the International Standard Industrial Classification (ISIC) of economic activities, were used to calculate mean daily working time of the entire population. We also obtained the comparable economic activity data for Canada, China, Japan, and Russia, which did not archive data with the ILO. In total, economic data were available for 139 countries, representing 86% of the world population.

Youth Population. While the time use surveys are nationally representative, many do not include youth below a minimum age, which varies by country between 14 and 18 y. The absence of children from most time use surveys can be generally attributed to the view of time use as a metric of human capital, a context in which children are not considered useful (44). In order to correct for the consequent bias, while also providing a complete description of human time, we assembled a complementary dataset on the time use of youth aged 0 to 17 y and used this to construct an age-structured model of total youth time. Student enrollment data from the World Bank and UNICEF were paired with educational instruction time from the OECD to calculate average daily time spent in schooling for each age. Youth employment data were taken from the 2016 ILO Global Estimates of Child Labour report, which covers children between ages 5 and 17 y in 105 countries and provides child employment rates in agriculture, industry, and services. Youth working hours were obtained from the World Bank. The activities occupying the remainder of average daily time were estimated using data averaged from time use studies conducted in 10 countries, as well as a global youth sleep time study (see *SI Appendix*, section 4 for details). Sensitivity tests without the youth model are provided in *SI Appendix*, section 9.

Sleep. Sleep, as recorded by wearable devices among >18-y-old adults, consumes 7.5 h per day, while the self-reported estimates averaged over all ages result in an average of 9.1 ± 0.4 h of sleep plus resting in bed, or being in bed but not sleeping. The 1.6 h discrepancy is partly attributable to the well-characterized overestimation of total sleep time in time diaries (45, 46). Prior comparisons of sleep time have found this difference to exceed 1 h (45) due to the inclusion of sleep onset latency, offset, nighttime waking, and other activities in the self-reported sleep time. In addition, youth, who are included in our global estimate but not the wearables data, generally sleep longer hours.

Activity Categories. Given the diversity of our data sources, it was necessary to crossmap across a large number of activity categorization systems, known as lexicons. Activities were reclassified according to the motivating outcomes that cause the activities to be undertaken, using the MOOGAL as described in ref. 29. The MOOGAL subcategories are intended to apply to any human population and epoch and are generally well aligned with commonly used sociological and economic lexicons (HETUS, ICATUS, ISIC) for the majority of activities. Activities that are coordinated between multiple people, such as those carried out in economic activities organized by firms, are categorized according to the motivating final output, consistent with standard economic practice. We apply a priority scheme such that Priority 1 subcategories are identified in preference to Priority 2 where both co-occur, and Priority 3 has the lowest priority. Thus, Priority 3 experience–oriented activities (e.g., reading) are only coded as such if they are not identified as contributing to a Priority 1 or Priority 2 outcome (e.g., schooling and research). Because activities are frequently reported in terms that include more than one MOOGAL outcome, our coding system allows fractional partitioning of an observed activity between MOOGAL subcategories. For a given lexicon of length n, each activity is associated to the 24 MOOGAL subcategories in an $n \times 24$ matrix by assigning a relative weight between 0 and 1 to each subcategory. These weightings indicate the portion of time from the original activity that is associated with the given subcategory, as estimated by human coders. A weighting of 1 indicates that the activity is uniquely associated with the single subcategory, while a weighting of 0 indicates that the activity is entirely excluded from that subcategory. An activity that cannot be entirely associated with a single subcategory is split fractionally among subcategories, that together sum to 1. All activity definitions were estimated independently by at least three coders, discrepancies were reviewed, and mean values were used wherever unequal but defensible estimates co-occurred.

Interpolation to Countries with Missing Data. Our dataset includes direct observations for 145 countries. Of these, both time use and economic data were available for 52 countries, time use data alone were available for 6 countries, and economic data alone were available for the remaining 87 countries. To assess the entire global human population, we group countries into 17 geographic regions based on the ILO subregions and separately interpolate both time use and economic data to the missing countries in each region. For each missing data type, countries are filled using the population-weighted average of the sampled countries in the same region, for each subcategory.

Data, Materials, and Software Availability. All data used in this work, as well as scripts to compile the results, are deposited in zenodo (10.5281/zenodo.7941615) (47).

ACKNOWLEDGMENTS. We thank Victoria Reyes-García, Jeroen Van Den Bergh, David Carozza, Dror Etzion, Majdi Hunter-Batal, Maxwell Kaye, Maria Pastor, Lior Greenspoon, Eric Kolaczyk and Brian Robinson for helpful comments and discussion.

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Supplementary Information for
"The Global Human Day"

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Contents

1 Method Overview

To construct the Global Human Day, we assembled national data from Time Use Surveys (TUS) with economic data from labor force surveys (LFS), and estimated time use among global youth using an age-structured model that combines education, labor and background time use data (Fig. S4).

TUS aim to provide holistic assessments of daily activities across the population, but typically group formal economic activities into a single work category (e.g., "paid employment"). Labour force surveys (LFS) enable us to resolve these formal economic work activities in detail. Both TUS and LFS are carried out by national governments with methodologies that vary between countries. Most importantly, the age ranges surveyed by TUS differ between countries, with lower bounds ranging from 5 to 18 years of age (Table S1, S2). A full and representative assessment of overall human time use can only be made by including the full age range, requiring additional sources to inform the youth component of the population where it is not captured by time use or labour force surveys. Each of these data sources and respective methodologies are described in further detail in Sections 2, 3 and 4.

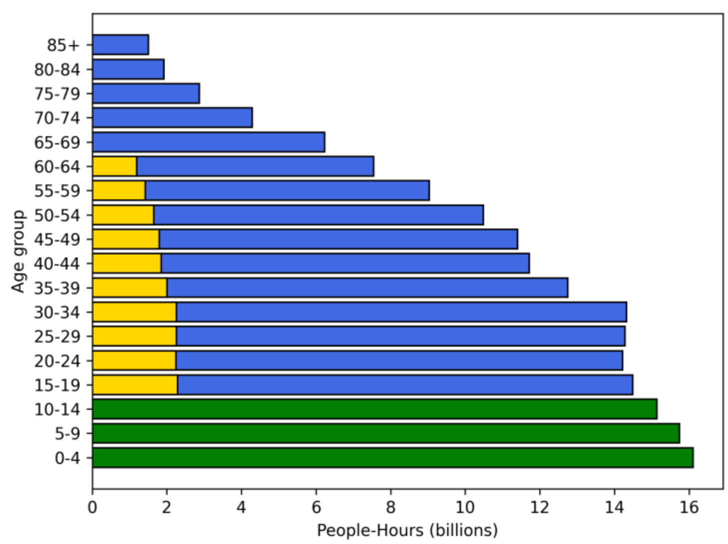
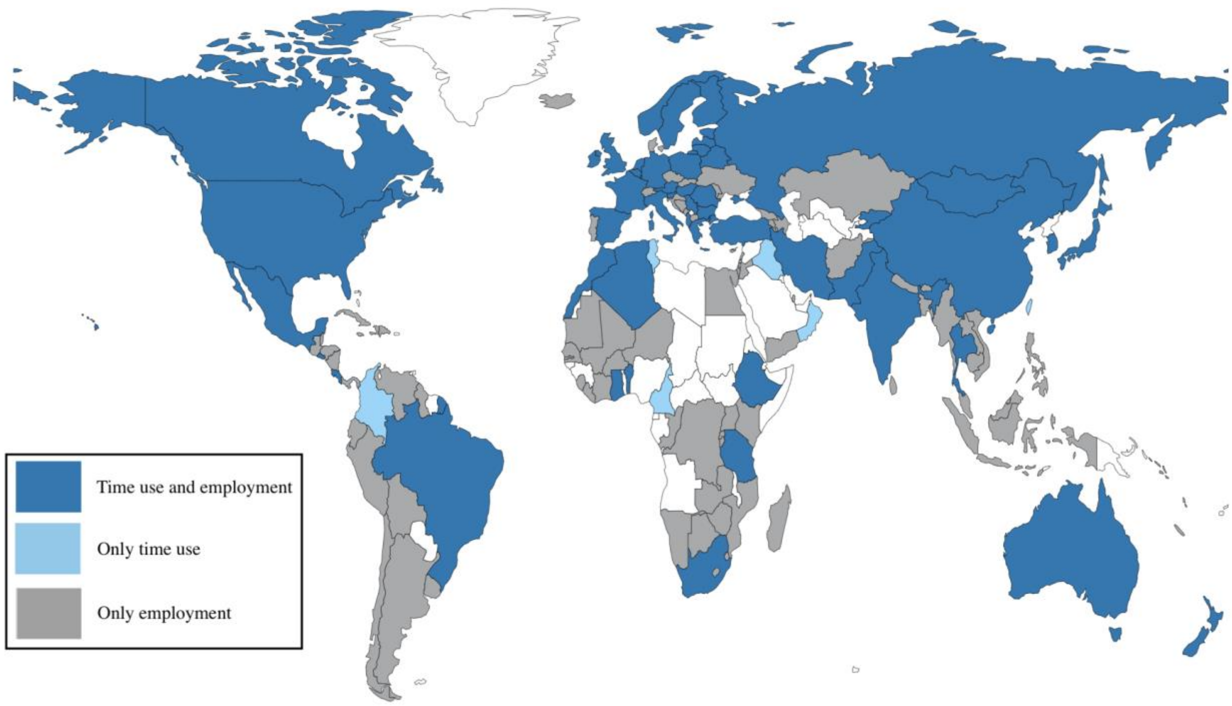


Fig. S1. Data constraints by age. Green represents the composite youth model (note that the upper age limit for this varies by country); yellow represents the portion constrained by economic labour data under the assumption that the total working time is proportionally distributed across the working-age population (15-64); blue represents the portion captured by time use surveys of the adult population.

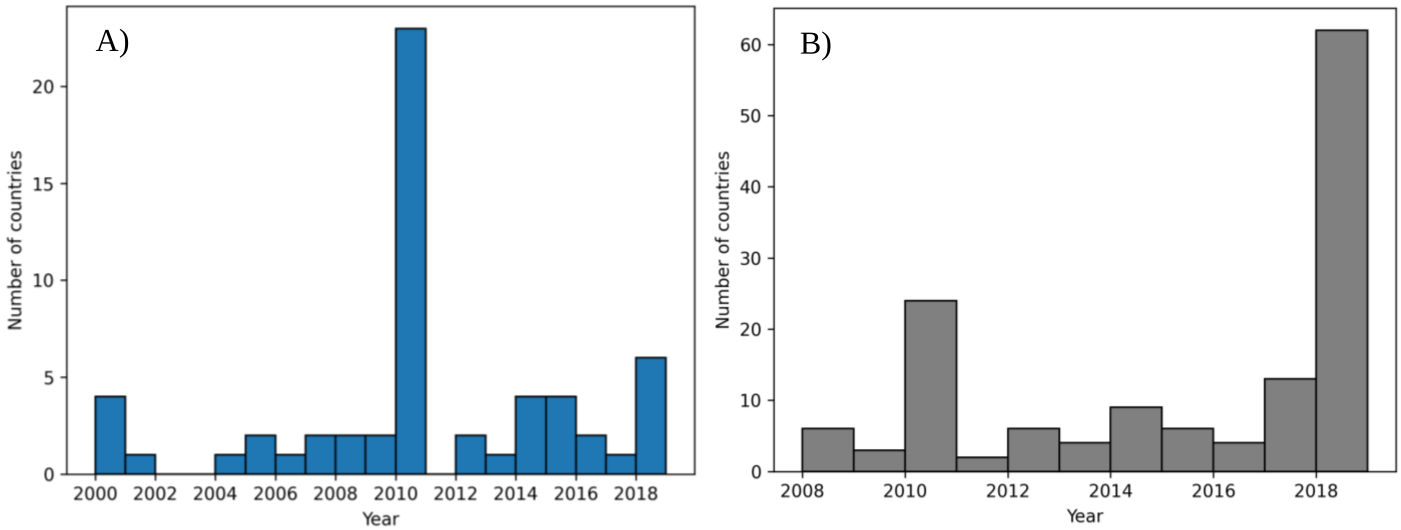
The geographical distributions for TUS and LFS are shown in Figure S2. In total, we use TUS data for 58 countries, representing 60% of the world population, and LFS data for 139 countries, representing 86% of the world population. For the countries without data, we estimate the corresponding activities (TUS, economic, or both) by interpolating regional means.

Fig. S2. Global coverage of time use surveys and economic data used in our analysis. Countries with no data are shown in white.



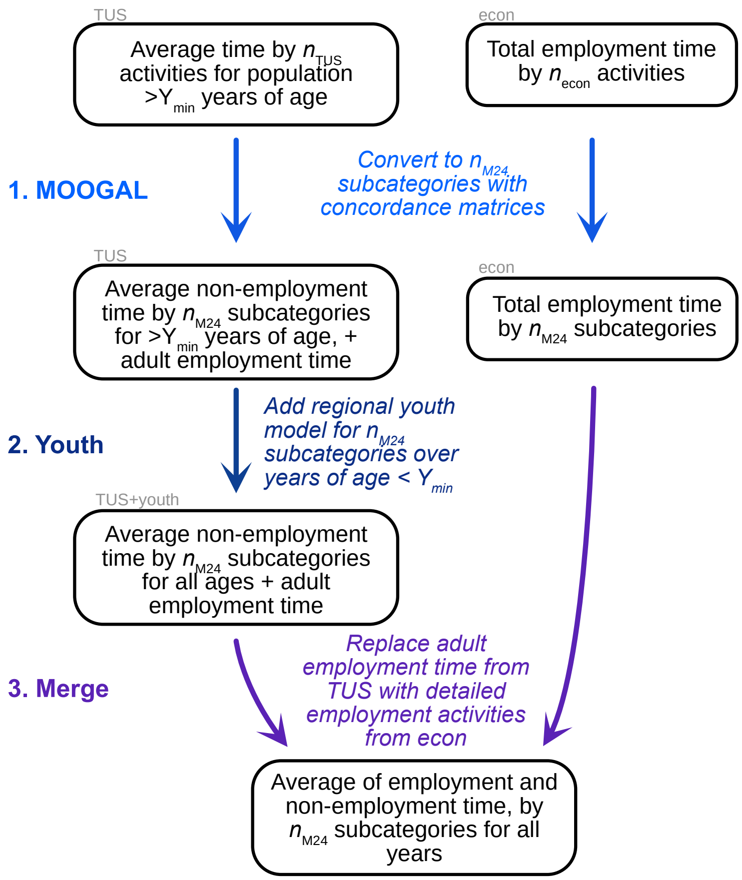
The temporal distribution of data spans 2000-2019, with the majority of data over the period 2010-2019, and with a larger proportion of economic data derived from 2018-2019. Conducting a TUS is a major undertaking, and most countries that endeavour to assess their citizens' time use do so no more than once per decade. In general, this low rate of sampling does not appear likely to be a problem, given the relatively slow evolution of time use within countries for which long timeseries are available (e.g. [1]). Three quarters of the TUS data used here were collected over the period 2010-2019, with the remaining quarter between 2000-2009, as shown in Fig. S3A. LFS are carried out more frequently, so that more than half of the datasets used here are from 2018-2019 (Fig. S3B).

Fig. S3. Distribution of years for time use surveys (A, *n=58*) and labor force surveys (B, *n=139*). The abundance of time use surveys in 2010 is due to the European Union's Harmonized European Time Use Survey (HETUS).



An overview of the workflow for harmonizing and combining datasets is shown in Figure S4. Each national TUS initially contained n_{TUS} activities, for the population older than Y_{min} years of age. Each national labor dataset initially contained n_{econ} activities for a total number of worker hours. The activities were converted to the 24 MOOGAL subcategories (the M24 lexicons) using concordance matrices as described in Section 5. The youth component was then integrated with the TUS, weighted by age-structured population sizes. After interpolation to fill missing data, the TUS and econ data were merged. Representative uncertainties were assessed at each of the three stages of the workflow, as described in Section 6.

Fig. S4. Workflow for computing the global human day.



2 Time Use Surveys

National time use surveys provide the most complete population-level time use data available and represent the largest overall contribution to our estimate of the global human day. The majority of time use surveys employ the time diary collection method, in which participants self-describe their activities in short (5-15 minute) intervals throughout the preceding 24h. This is recognized as the highest quality and most reliable method for time use surveys [2]. Modifications to this approach are often found in many lower-income countries, where field teams are employed to conduct in-person interviews due to low literacy rates, remoteness of rural households, and technical and cultural barriers [3], [4]. Functionally, the interview method is largely comparable to a time diary, where the interviewers fill in the diaries on a recall basis with the household member(s). All surveys have the common aim of capturing respondents' daily time allocated to a set of particular activities. Data collection is often spread out over time to capture temporal variation in time use. National agencies then apply statistical weighting to ensure that the survey is as representative as possible of the entire population and temporal period. For the characteristics of the surveys used, see Table S1. In total, we include time use data for 58 countries, covering 60% of the current world population (Table S1; Fig. S2).

Table S1 – Selected characteristics of time use surveys and assessed quality score. Quality is ranked from A (relatively high quality) to C (relatively low quality), based on features of the survey, as described in section 7.2 and Table S6. Lexicon length refers to the number of activities in the survey activity categorization, as discussed in section 5.

Country	Region	Survey Year	Age Range	Survey Timespan	Data Collection Method	Lexicon Length	Assessed Quality	Source
Albania	Southern Europe	2010	10+	1 year	10 minute diary	28	A	[5]
Australia	Australia and New Zealand	2006	15+	1 year	5 minute diary	61	A	[6]
Austria	Western Europe	2010	15+	1 year	10 minute diary	49	A	[7]
Belgium	Western Europe	2010	15+	1 year	10 minute diary	49	A	[7]
Benin	Western Africa	2015	6-64	4 months	Interview, 5 activities per hour	53	B	[8]
Bulgaria	Eastern Europe	2000	15+	1 year	10 minute diary	49	A	[7]
Belarus	Eastern Europe	2014	10+	1 year	10 minute diary	23	A	[9]
Brazil	South America	2001	18-64	Unknown	Unknown	31	C	[10]
Canada	North America	2015	15+	1 year	Diary & interview	19	A	[11]
China	Eastern Asia	2008	15-74	1 month	Diary	115	B	[12]

Country	Region	Survey Year	Age Range	Survey Timespan	Data Collection Method	Lexicon Length	Assessed Quality	Source
Cameroon	Middle Africa	2014	10+	Unknown	Interview	51	B	[13]
Colombia	South America	2016	10+	1 year	Interview	20	B	[14]
Costa Rica	Central America	2017	12+	Unknown	Unknown	19	C	[15]
Germany	Western Europe	2010	15+	1 year	10 minute diary	49	A	[7]
Algeria	Northern Africa	2012	12+	2 months	Interview	36	B	[16]
Spain	Southern Europe	2010	15+	1 year	10 minute diary	49	A	[7]
Estonia	Northern Europe	2010	15+	1 year	10 minute diary	49	A	[7]
Ethiopia	Eastern Africa	2014	10+	1 month	Interview, 5 activities per hour	15	B	[17]
Finland	Northern Europe	2010	15+	1 year	10 minute diary	49	A	[7]
France	Western Europe	2010	15+	1 year	10 minute diary	49	A	[7]
Great Britain	Western Europe	2010	15+	1 year	10 minute diary	49	A	[7]
Ghana	Western Africa	2009	10+	1.5 months	Interview, 5 activities per hour	15	B	[18]
Greece	Southern Europe	2010	15+	1 year	10 minute diary	49	A	[7]
Hungary	Eastern Europe	2010	15+	1 year	10 minute diary	49	A	[7]
India	Southern Asia	2019	6+	1 year	Interview, 30 minute slots max 3 activities each	165	A	[4]
Ireland	Western Europe	2005	18+	2.5 months	15 minute diary	27	B	[19]
Iran	Southern Asia	2019	15+	1 year	Unknown	9	B	[20]
Iraq	Western Asia	2007	10+	1 month	Interview	27	B	[21]
Italy	Southern Europe	2010	15+	1 year	10 minute diary	49	A	[7]
Japan	Eastern Asia	2016	10+	9 days over year	Diary & interview	20	B	[22]
Kyrgyzstan	Central Asia	2010	12+	Unknown	Interview	10	C	[23]
South Korea	Eastern Asia	2014	10+	2 months	10 minute diary	123	B	[24]
Lithuania	Northern Europe	2000	15+	1 year	10 minute diary	49	A	[7]
Luxembourg	Western Europe	2010	15+	1 year	10 minute diary	49	A	[7]
Latvia	Northern Europe	2000	15+	1 year	10 minute diary	49	A	[7]
Morocco	Northern Africa	2012	15+	1 year	Interview	42	A	[25]
Mexico	Central America	2019	12+	2 months	Diary	37	B	[26]
Mongolia	Eastern Asia	2015	15+	1 year	Diary & interview	8	B	[27]
Mauritius	Eastern Africa	2018	12+	1 year	15 minute diary	24	A	[28]
Netherlands	Western Europe	2010	15+	1 year	10 minute diary	49	A	[7]
Norway	Northern Europe	2010	15+	1 year	10 minute diary	49	A	[7]
New Zealand	Australia and New Zealand	2009	12+	1 year	Diary	69	A	[29]
Oman	Western Asia	2008	15+	1 year	15 minute diary	25	A	[30]
Pakistan	Southern Asia	2007	0+	1 year	Interview, 30 minute slots max 3 activities each	123	A	[31]
Poland	Eastern Europe	2010	15+	1 year	10 minute diary	49	A	[7]

Country	Region	Survey Year	Age Range	Survey Timespan	Data Collection Method	Lexicon Length	Assessed Quality	Source
Romania	Eastern Europe	2010	15+	1 year	10 minute diary	49	A	[7]
Russia	Eastern Europe	2019	15+	Unknown	Unknown	11	C	[32]
El Salvador	Central America	2010	10+	Unknown	Interview	14	C	[33]
Serbia	Southern Europe	2010	15+	1 year	10 minute diary	49	A	[7]
Slovenia	Southern Europe	2000	15+	1 year	10 minute diary	49	A	[7]
Sweden	Northern Europe	2010	19+	1year	10 minute diary	101	A	[34]
Thailand	South-eastern Asia	2015	10+	Unknown	Unknown	15	C	[35]
Tunisia	Northern Africa	2005	15+	1 year	Diary	43	A	[36]
Turkey	Western Asia	2010	15+	1 year	10 minute diary	49	A	[7]
Taiwan	Eastern Asia	2004	15+	2 month	Diary	20	B	[37]
Tanzania	Eastern Africa	2014	5+	1 year	Interview	15	A	[38]
United States of America	North America	2019	15+	1 year	10 minute diary	89	A	[39]
South Africa	Southern Africa	2010	10+	3 months	Interview, 30 minute slots	104	B	[40]

2.1 Data Collection and Processing

Aggregate survey data was downloaded from national statistical agency databases where available and translated to English as necessary. If the aggregated datafile was not provided, written reports were downloaded and manually digitized. Data for Algeria, Iraq, Mauritius, and Oman were previously assembled by a co-author of this paper (JC). Only nationally representative surveys conducted prior to 2020 were used.

Time use survey data is reported according to a hierarchical activity classification, most frequently composed of two levels: a general class of activity ("tier 1") and a more specific class ("tier 2"). As such, all files were modified to follow the same format of three columns: tier 1 activity, tier 2 activity, and average hours per day. Surveys that reported time in minutes, in clock notation (e.g., 0:05 for 5 minutes, 1:30 for 1 hour and 30 minutes), or in hours per week were converted to decimal hours per day. The population average time use was summed, and where this was not exactly equal to 24.0h, all activities were proportionally adjusted to sum to 24.0h. Surveys where the sum of activities differed from 24.0h by more than 0.5 h were not used due to reliability concerns.

2.2 Special Cases

Three surveys reported data for the male and female population separately, without providing average time per activity for the total population. We calculated the total population weighted average for these countries using gender proportions reported in the surveys as follows:

Costa Rica 2017: 49.7% female, 50.3% male.

Mongolia 2015: 51.5% female, 48.5% male.

Mauritius 2018: 54% female, 46% male.

A further 4 surveys reported data in non-standard formats, requiring recalculation to provide total population-weighted averages as follows:

Algeria 2012: Data were reported by urban and rural population separately. A population weighted average was calculated using the relative proportion of urban and rural households in the survey (67.6% urban, 32.4% rural, which closely matches the urban and rural population split in data provided by the UN Department of Economic and Social Affairs [41]).

Ireland 2005: Tier 1 data were reported by weekday and weekend averages. We calculated a weighted average using 5/7 and 2/7 for the weights for weekdays and weekends, respectively. Tier 2 data were reported as 'long days', meaning simultaneous activities are included. We correct for this by reweighting each tier 2 activity by the ratio of time in the corresponding tier 1 category to the sum of 'long day' time in all corresponding tier 2 activities, $T_2(adjusted) = T_2 * (\frac{T_1}{\sum T_2})$

Mexico 2019: Hours were reported as total aggregate person-hours. These figures were divided by the total represented population to produce average daily hours per person.

El Salvador 2010: Only participant time and participation rate were reported, despite the participant time being labeled "average hours." This was evident from the fact that the sum of participant time is much greater than 24.0 hours. Average daily hours per person were therefore calculated by multiplying the participant time by the participation rate, which resulted in a correct total time of 24.0 hours.

3 Employment Data

The formal economic activities that make up the "work" component of time use surveys were resolved using labour force survey data. Economic activity data for 135 countries were obtained from the International Labour Organization (ILO) statistics database, ILOSTAT. Specifically, we use datasets on employment and working time according to the International Standard Industrial Classification (ISIC) lexicon, a system developed by the United Nations that categorizes jobs into economic activities within the framework of the System of National Accounts (SNA). The following datasets were download from ILOSTAT:

- Mean annual employment by sex and economic activity - ISIC level 2 [42];
- Mean weekly hours actually worked per employed person by sex and economic activity - ISIC level 2 [43];
- Mean annual employment by sex and economic activity - ISIC level 1 [44];
- Mean weekly hours actually worked per employed person by sex and economic activity – ISIC level 1 [45].

In addition, the following two datasets were used to verify the accuracy of the ISIC statistics:

- Labour force by sex and age - ILO modelled estimates [46];
- Unemployment by sex and age – ILO modelled estimates [47].

We also obtained economic activity data for four countries in our analysis that had time use surveys but no economic activity data available via ILOSTAT: Canada [48], China [49], Japan [50], and Russia [51]. The requisite economic activity data (i.e., employment and average hours actually worked) for these countries were obtained directly from national statistical repositories or reports (see Table S3). In total, we include economic activity data from labour force surveys for 139 countries, covering 86% of the current world population (Fig. S2).

Table S2 – Selected characteristics of economic activity data from labor force surveys archived with the International Labour Organization. We use data categorized according to the International Standard Industrial Classification (ISIC). Labor Force Covered refers to the fraction of the labor force represented in employment and unemployment statistics (see section 3.2).

Country	Region	Year	Labour Force Covered	ISIC Version	ISIC Level	Age Range	Reference Period	Population Coverage
Afghanistan	Southern Asia	2017	1.00	Rev.4	Level 2	15+	Annual	National
Albania	Southern Europe	2014	1.00	Rev.4	Level 2	15+	Annual	National
Algeria	Northern Africa	2017	1.00	Rev.4	Level 1	15+	September	National
Argentina	South America	2019	1.00	Rev.4	Level 1	15+	Annual	Main cities or metropolitan areas
Armenia	Western Asia	2015	1.06	Rev.4	Level 2	15-75	Annual	National
Aruba	Central America	2010	1.00	Rev.3.1	Level 1	14+	September	National

Country	Region	Year	Labour Force Covered	ISIC Version	ISIC Level	Age Range	Reference Period	Population Coverage
Australia	Australia and New Zealand	2008	1.00	Rev.4	Level 1	15+	August	Total national, excluding overseas territories; excluding both institutional population and armed forces and/or conscripts
Austria	Western Europe	2011	1.00	Rev.4	Level 2	Unknown	Annual	National
Azerbaijan	Western Asia	2019	1.00	Rev.4	Level 1	15+	End of year	Excluding own-use production workers, institutional population and armed forces and/or conscripts
Bangladesh	Southern Asia	2017	1.00	Rev.4	Level 2	15+	Annual	National
Belarus	Eastern Europe	2016	1.00	Rev.4	Level 2	15-74	Annual	National
Belgium	Western Europe	2010	1.00	Rev.4	Level 2	15+	Annual	National
Belize	Central America	2019	1.00	Rev.4	Level 1	15+	Annual	National
Benin	Western Africa	2010	1.00	Rev.4	Level 1	15-64	Annual	National
Bhutan	Southern Asia	2019	1.00	Rev.4	Level 2	15+	Annual	National
Bolivia	South America	2019	1.00	Rev.4	Level 1	15+	Annual	National
Bosnia and Herzegovina	Southern Europe	2019	1.00	Rev.4	Level 2	15+	Annual	National
Botswana	Southern Africa	2019	1.00	Rev.4	Level 2	15+	Annual	National
Brazil	South America	2012	1.00	Rev.4	Level 2	15+	Annual	National
Brunei	South-eastern Asia	2019	1.00	Rev.4	Level 2	15+	Annual	National
Bulgaria	Eastern Europe	2008	0.99	Rev.4	Level 2	15+	Annual	National
Burkina Faso	Western Africa	2014	1.00	Rev.3.1	Level 1	15+	Annual	National
Burundi	Eastern Africa	2014	1.00	Rev.4	Level 2	10+	Annual	National
Cambodia	South-eastern Asia	2019	1.00	Rev.4	Level 2	15+	Annual	National
Chile	South America	2019	1.00	Rev.4	Level 1	15+	Annual	National
Comoros	Eastern Africa	2014	0.99	Rev.4	Level 2	15+	Annual	National
Costa Rica	Central America	2017	1.00	Rev.4	Level 2	15+	Annual	National
Cote d'Ivoire	Western Africa	2019	1.00	Rev.4	Level 2	15+	Annual	National
Croatia	Southern Europe	2019	1.00	Rev.4	Level 2	15+	Annual	National
Cuba	Central America	2010	0.94	Rev.4	Level 1	17+	Annual	National
Cyprus	Western Asia	2019	1.00	Rev.4	Level 2	9+	Annual	National
Czechia	Eastern Europe	2019	1.00	Rev.4	Level 2	15+	Annual	National
Democratic Republic of the Congo	Middle Africa	2012	1.00	Rev.4	Level 2	15+	Annual	National
Denmark	Northern Europe	2019	1.00	Rev.4	Level 2	15+	Annual	National
Dominican Republic	Central America	2019	1.00	Rev.4	Level 2	15+	Annual	National
Ecuador	South America	2014	1.00	Rev.4	Level 2	15+	Annual	National
Egypt	Northern Africa	2019	1.00	Rev.4	Level 2	15+	Annual	National
El Salvador	Central America	2010	1.00	Rev.4	Level 2	16+	Annual	National

Country	Region	Year	Labour Force Covered	ISIC Version	ISIC Level	Age Range	Reference Period	Population Coverage
Estonia	Northern Europe	2010	0.98	Rev.4	Level 2	15+	Annual	National
Ethiopia	Eastern Africa	2013	1.00	Rev.4	Level 2	15+	Annual	National
Finland	Northern Europe	2010	1.00	Rev.4	Level 2	15+	Annual	National
France	Western Europe	2010	1.00	Rev.4	Level 2	15+	Annual	National
Georgia	Western Asia	2019	1.00	Rev.4	Level 2	15+	Annual	National
Germany	Western Europe	2010	1.00	Rev.4	Level 2	15+	Annual	National
Ghana	Western Africa	2013	1.00	Rev.4	Level 2	15+	Annual	National
Great Britain	Northern Europe	2010	1.00	Rev.4	Level 2	15+	Annual	National
Greece	Southern Europe	2010	1.00	Rev.4	Level 2	15+	Annual	National
Guatemala	Central America	2016	1.00	Rev.4	Level 1	15+	1st quarter	National
Guyana	South America	2019	1.00	Rev.4	Level 2	15+	Third quarter	National
Haiti	Central America	2012	1.02	Rev.4	Level 1	15+	Annual	National
Honduras	Central America	2019	0.98	Rev.4	Level 2	15+	Second quarter	National
Hong Kong	Eastern Asia	2009	1.00	Rev.4	Level 1	15+	Annual	Excluding institutional population
Hungary	Eastern Europe	2010	1.00	Rev.4	Level 2	15+	Annual	National
Iceland	Northern Europe	2019	0.97	Rev.4	Level 2	15+	Annual	National
India	Southern Asia	2019	1.00	Rev.4	Level 2	15+	Annual	National
Indonesia	South-eastern Asia	2015	1.00	Rev.4	Level 2	15+	Annual	National
Iran	Southern Asia	2019	1.00	Rev.4	Level 2	15+	Annual	National
Ireland	Northern Europe	2008	1.00	Rev.4	Level 2	15+	Annual	National
Israel	Western Asia	2017	1.00	Rev.4	Level 2	15+	Annual	National
Italy	Southern Europe	2010	1.00	Rev.4	Level 2	15+	Annual	National
Jamaica	Central America	2019	1.00	Rev.4	Level 1	15+	Annual	National
Jordan	Western Asia	2019	1.00	Rev.4	Level 2	15+	Annual	National
Kazakhstan	Central Asia	2017	1.00	Rev.4	Level 1	15+	Annual	Excluding own-use production workers, institutional population and armed forces and/or conscripts
Kenya	Eastern Africa	2019	1.00	Rev.4	Level 2	15+	Annual	National
Kyrgyzstan	Central Asia	2010	1.00	Rev.4	Level 2	15+	Annual	National
Laos	South-eastern Asia	2017	1.00	Rev.4	Level 2	15+	Annual	National
Latvia	Northern Europe	2008	0.99	Rev.4	Level 2	15+	Annual	National
Lebanon	Western Asia	2019	1.00	Rev.4	Level 2	15+	Annual	National
Lesotho	Southern Africa	2019	1.00	Rev.4	Level 1	10-75	Annual	National
Liberia	Western Africa	2017	1.00	Rev.4	Level 2	15+	Annual	National
Lithuania	Northern Europe	2008	0.92	Rev.4	Level 2	15+	Annual	National
Luxembourg	Western Europe	2010	0.97	Rev.4	Level 2	15+	Annual	National
Macedonia	Southern Europe	2019	1.00	Rev.4	Level 2	15+	Annual	National
Madagascar	Eastern Africa	2015	0.99	Rev.4	Level 2	15+	Annual	National

Country	Region	Year	Labour Force Covered	ISIC Version	ISIC Level	Age Range	Reference Period	Population Coverage
Malaysia	South-eastern Asia	2019	1.00	Rev.4	Level 1	15-64	Annual	Excluding own-use production workers
Maldives	Southern Asia	2019	1.00	Rev.4	Level 2	15+	Annual	National
Mali	Western Africa	2018	1.00	Rev.4	Level 2	15+	Annual	National
Malta	Southern Europe	2019	0.99	Rev.4	Level 2	15+	Annual	National
Mauritania	Western Africa	2019	1.00	Rev.4	Level 2	10+	Annual	National
Mauritius	Eastern Africa	2018	1.00	Rev.4	Level 2	16+	Annual	National
Mexico	Central America	2019	1.00	Rev.4	Level 2	15+	Annual	National
Moldova	Eastern Europe	2019	1.00	Rev.4	Level 1	15+	Annual	National
Mongolia	Eastern Asia	2019	0.96	Rev.4	Level 2	15+	Annual	National
Montenegro	Southern Europe	2019	1.00	Rev.4	Level 1	15+	Annual	National
Morocco	Northern Africa	2012	1.00	Rev.3.1	Level 1	15+	Annual	National
Mozambique	Eastern Africa	2015	1.00	Rev.4	Level 2	15+	Annual	National
Myanmar	South-eastern Asia	2019	1.00	Rev.4	Level 2	15+	Annual	National
Namibia	Southern Africa	2018	1.00	Rev.4	Level 2	15+	Annual	National
Nepal	Southern Asia	2017	1.00	Rev.4	Level 2	15+	Annual	National
Netherlands	Western Europe	2010	1.00	Rev.4	Level 2	15+	Annual	National
New Caledonia	South-eastern Asia	2019	0.98	Rev.4	Level 2	15+	Annual	National
New Zealand	Australia and New Zealand	2009	1.01	Rev.4	Level 1	15+	Annual	Total national, excluding overseas territories; excluding both institutional population and armed forces and/or conscripts
Nicaragua	Central America	2012	1.00	Rev.3.1	Level 1	15+	Annual	National
Niger	Western Africa	2017	0.99	Rev.4	Level 2	15+	Annual	Excluding own-use production workers
Norway	Northern Europe	2010	1.00	Rev.4	Level 2	15+	Annual	National
Pakistan	Southern Asia	2013	1.00	Rev.4	Level 2	15+	Annual	National
Palestine	Western Asia	2019	1.00	Rev.4	Level 2	15+	Annual	National
Panama	Central America	2014	1.00	Rev.4	Level 2	15+	August	National
Peru	South America	2019	1.00	Rev.4	Level 2	15+	Annual	National
Philippines	South-eastern Asia	2019	1.00	Rev.4	Level 2	15+	Annual	National
Poland	Eastern Europe	2010	1.00	Rev.4	Level 2	15+	Annual	National
Portugal	Southern Europe	2019	1.00	Rev.4	Level 2	15+	Annual	National
Qatar	Western Asia	2019	1.00	Rev.4	Level 1	15+	September	Excluding own-use production workers
Republic of the Congo	Middle Africa	2009	1.00	Rev.4	Level 2	15+	Annual	Urban areas only
Romania	Eastern Europe	2010	1.00	Rev.4	Level 2	15+	Annual	National
Rwanda	Eastern Africa	2018	1.00	Rev.4	Level 2	15+	Annual	National
Saint Lucia	Central America	2019	1.00	Rev.4	Level 1	Unknown	Annual	National
Senegal	Western Africa	2019	1.00	Rev.4	Level 2	15+	Annual	National
Serbia	Southern Europe	2011	1.00	Rev.4	Level 2	15+	Annual	National

Country	Region	Year	Labour Force Covered	ISIC Version	ISIC Level	Age Range	Reference Period	Population Coverage
Sierra Leone	Western Africa	2018	1.00	Rev.4	Level 2	15+	Annual	National
Slovakia	Eastern Europe	2019	1.00	Rev.4	Level 2	15+	Annual	Excluding own-use production workers
Slovenia	Southern Europe	2008	1.00	Rev.4	Level 2	15+	Annual	National
Solomon Islands	South-eastern Asia	2013	1.00	Rev.4	Level 2	Unknown	Annual	National
South Africa	Southern Africa	2010	1.00	Rev.3.1	Level 1	15+	Annual	National
South Korea	Eastern Asia	2014	1.00	Rev.4	Level 1	15+	Annual	National
Spain	Southern Europe	2010	1.00	Rev.4	Level 2	15+	Annual	National
Sri Lanka	Southern Asia	2019	1.00	Rev.4	Level 2	15+	Annual	National
Swaziland	Southern Africa	2016	0.96	Rev.4	Level 2	15+	Annual	National
Sweden	Northern Europe	2010	1.00	Rev.4	Level 2	15+	Annual	National
Switzerland	Western Europe	2019	1.00	Rev.4	Level 2	15+	Annual	National
Tanzania	Eastern Africa	2014	1.00	Rev.4	Level 2	15+	Annual	National
Thailand	South-eastern Asia	2015	1.00	Rev.4	Level 2	15+	Annual	National
The Gambia	Western Africa	2012	1.00	Rev.4	Level 2	15+	Annual	National
Tonga	South-eastern Asia	2018	1.00	Rev.4	Level 2	15+	Annual	National
Turkey	Western Asia	2010	1.00	Rev.4	Level 2	15+	Annual	National
Uganda	Eastern Africa	2017	1.00	Rev.4	Level 2	15+	Annual	National
Ukraine	Eastern Europe	2017	1.00	Rev.4	Level 1	15-70	Annual	Including subsistence workers, excluding both institutional population and armed forces and/or conscripts
United States of America	Northern America	2019	1.00	Rev.4	Level 2	16+	Annual	National
Uruguay	South America	2018	1.00	Rev.4	Level 1	15+	Annual	Urban areas only
Vanuatu	South-eastern Asia	2019	0.99	Rev.4	Level 2	15+	Annual	National
Venezuela	South America	2017	1.00	Rev.3.1	Level 1	15+	Annual	National
Viet Nam	South-eastern Asia	2019	1.00	Rev.4	Level 2	15+	Annual	Excluding own-use production workers
Yemen	Western Asia	2014	1.00	Rev.3.1	Level 1	15+	Annual	National
Zambia	Eastern Africa	2019	1.00	Rev.4	Level 2	15+	Annual	National
Zimbabwe	Eastern Africa	2019	1.00	Rev.4	Level 2	15+	Annual	National

Table S3 – Selected characteristics of economic activity data from unique sources not available from the International Labour Organization.

Country	Region	Year	Labour Force Covered	Classification	Age Range	Reference Period	Population Coverage

Canada	North America	2015	0.99	North American Industrial Classification System (NAICS)	15+	Annual	National
China	Eastern Asia	2010	0.94	Own classification	15-64	Annual	National
Japan	Eastern Asia	2016	0.99	Japanese Standard Industrial Classification System	15+	Annual	National
Russia	Eastern Europe	2018	1.0	Own classification	15-64	Annual	National

3.1 Data Processing and Quality Control

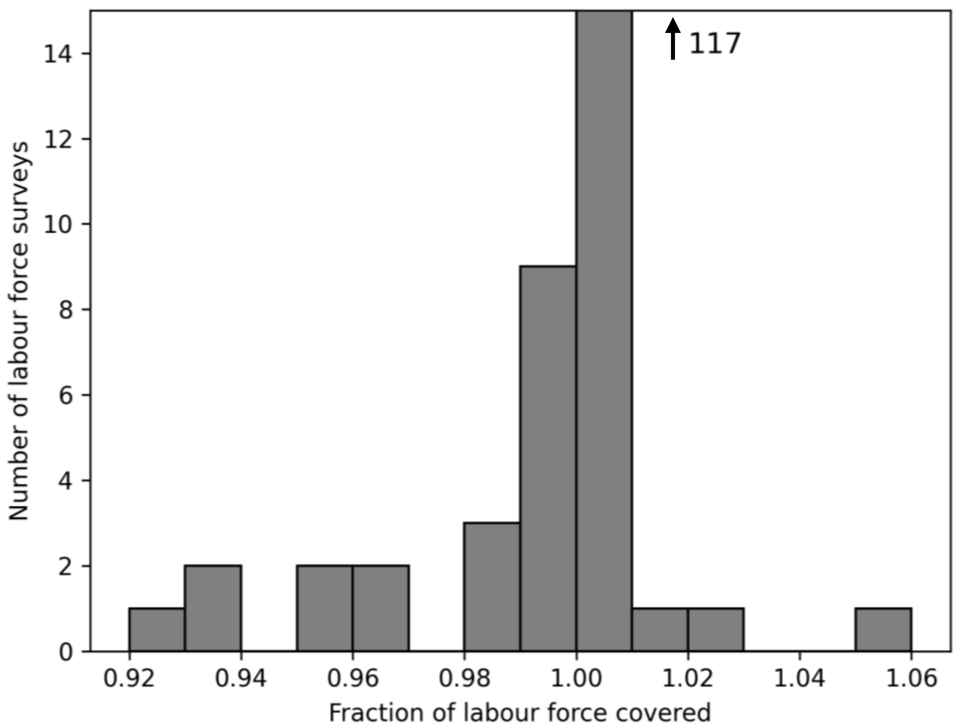
Employment data were reported in units of thousands of people, and working time was reported in units of mean hours per week. Employment was converted to total number of people and mean weekly working time converted to mean daily working time. For each country, we chose the survey year based on three criteria: sufficient labour force coverage, highest level of activity resolution possible, and (if applicable) temporal proximity to the time use survey.

We then evaluated the employment data based on labour force coverage. A country's labour force (L) is generally defined as the sum of all working-age people who are either employed (E) or not employed but looking for work (unemployed, U). Thus, $L = E + U$, or $\frac{E+U}{L} = 1$. We calculated this labour force coverage fraction for each survey to ensure that the employment data is consistent with the ILO estimate of the labour force. Discrepancies exist due to incomplete geographical or temporal survey coverage resulting in under-representation of workers in certain sectors, or due to inconsistencies in the definition of employment used in the employment dataset and labour force size dataset. To avoid introducing errors we excluded surveys for which the fraction of the labour force covered is less than 0.9 or greater than 1.1. The frequency distribution of labour force coverage for all country-years used is shown in Fig. S5, and values listed in Table S2. Overall, 126 of the countries show < 1% disagreement between the employment data and the labour force estimate.

We took the most detailed level of ISIC activity classification available: ISIC Revision 4 Level 2 for 104 countries, ISIC Revision 4 Level 1 for 24 countries, and ISIC Revision 3.1 Level 1 for the remaining 7 countries (see Table S2). We chose the specific year of economic activity data based on whether the country has a time use survey or not. For countries with time use surveys, we maximize internal consistency by using the economic data from year closest to the time use survey. For all other countries, we use the most recent year available up to 2019, given the above-mentioned conditions.

Four countries with time use surveys did not have economic activity data available on ILOSTAT: Canada, China, Japan, and Russia. For these countries, we downloaded the requisite data from the appropriate national statistics agency, following the same criteria discussed above (i.e., sufficient labour force coverage, most detailed classification available, and year nearest the time use survey) (see Table S3).

Fig. S5. Distribution of labour force coverage among all economic activity data, where the fraction of the labour force covered is calculated as the sum of individuals in employment and unemployment, divided by the labour force.



4 Youth data

Time use surveys are nationally representative, but most do not include youth below a minimum age Y_{min}, which varies by country between 5 and 18 years (Table S1). In order to provide a complete description of human time, we developed an age-structured model of time use by youths from 0-18 years. As detailed below, student enrollment data were paired with educational instruction time to calculate average daily time spent in schooling for each age and combined with youth employment data. The activities occupying the remainder of time were estimated by using youth time use studies and a global youth sleep time study to define a set of fixed-time activities and proportional-time activities. The overall features of the global human day are relatively insensitive to the inclusion of the youth model, as shown in Section 9.

4.1 Schooling data

Nearly all children participate in formal schooling for at least part of their youth, and basic education statistics are widely available. We combined country-specific enrolment rate and daily school time data for each 1-year age bin from 0 to 18 to estimate annual mean daily school time.

Enrolment rates are provided for primary schooling, lower secondary schooling, and upper secondary schooling. These categories correspond to the International Standard Classification of Education (ISCED) system, in which ISCED 1 refers to primary school, and ISCED 2 and 3 refer to lower and upper secondary school, respectively. ISCED categories are not associated with specific age ranges, so we associated schooling statistics with annual age bins using national data on the ISCED level start age and school duration. Data on the ISCED 1 starting age [52], ISCED 2 starting age [53], and secondary education duration [54] were collected by the UNESCO educational survey and disseminated by the World Bank for all countries. On average, ISCED 1 begins at age 6, while ISCED 2 begins at age 12.

National enrolment data were retrieved from the World Bank and UNICEF databases (Table S4). From the World Bank, we used the net adjusted enrolment for ISCED 1, which is the percentage of students of the age for primary education enrolled in primary or secondary education for ISCED 1 [55]. Only net enrolment was available for ISCED 2 and 3 [56], which is the ratio of enrolled school-age children to all school age children and excludes children attending a different educational level than expected for their age, a minor factor (approximately 1% of total enrolment). UNICEF reports a net adjusted attendance rate, defined as the percentage all official-school-age children attending primary or secondary school for non-OECD countries derived from country-level household surveys disseminated by multiple organizations. The UNICEF net adjusted attendance data covers ISCED 1, 2, and 3.

The enrolment/attendance statistics are summarized in Table S4. The enrolment and attendance rates generally agree well with each other where both are >90%, but there are large discrepancies for a number of countries in which one or both indicators are low. As a result, we used the average of the two indicators for each country.

Table S4. Summary of youth rates of enrolment/attendance at school. All rates are displayed as percentages. The UNICEF net adjusted attendance rate and World Bank adjusted net enrolment were averaged for use in the youth model.

Country	ILO Sub Region	ISCED 1 World Bank Net Adjusted Enrolment[55]	UNICEF Net Adjusted Attendance[57]	ISCED 2 & 3 World Bank Net Enrolment[56]	UNICEF Net Adjusted Attendance[57]
Afghanistan	Southern Asia	26.77	63.70	50.14	33.15
Albania	Southern Europe	97.44		86.61	
Algeria	Northern Africa	99.65	97.50	52.93	62.70
Angola	Middle Africa	81.60	75.80	11.29	30.70
Antigua and Barbuda	Caribbean	99.31		88.79	
Argentina	South America	99.48	98.60	90.80	76.00
Armenia	Western Asia	90.84	95.43	87.74	89.68
Aruba	Caribbean	99.29		76.95	
Australia	Australia and New Zealand	96.50		96.86	
Austria	Western Europe	88.64		87.00	
Azerbaijan	Western Asia	92.62	67.70	88.53	
Bahamas, The	Caribbean	74.39		62.50	
Bahrain	Western Asia	98.10		90.19	
Bangladesh	Southern Asia	94.96	85.90	66.55	52.95
Barbados	Caribbean	98.39	99.47	93.63	85.45
Belarus	Eastern Europe	95.21	91.70	95.64	91.80
Belgium	Western Europe	99.11		94.95	
Belize	Central America	99.01	95.80	71.15	28.60
Benin	Western Africa	97.21	68.30	46.58	21.10
Bermuda	Northern America	92.71		72.77	
Bhutan	Southern Asia	90.07	95.20	70.20	38.25
Bolivia	South America	93.18		76.55	
Bosnia and Herzegovina	Southern Europe		96.06		93.45
Botswana	Southern Africa	88.26	90.00	59.79	
Brazil	South America	97.55	93.93	81.73	75.08
British Virgin Islands		93.82		68.11	
Brunei Darussalam	South-eastern Asia	96.08		82.65	
Bulgaria	Eastern Europe	88.09		89.06	
Burkina Faso	Western Africa	79.34	51.90	31.00	11.30
Burundi	Eastern Africa	93.42	82.11	27.52	18.11
Cabo Verde	Western Africa	93.53		70.43	
Cambodia	South-eastern Asia	90.69	92.83	38.33	38.40
Cameroon	Middle Africa	92.87	83.99	45.99	40.04
Canada	Northern America	99.96		99.81	
Central African Republic	Middle Africa	64.17	73.30	12.72	9.70
Chad	Middle Africa	73.47	50.30	18.86	10.65
Chile	South America	94.78	88.80	88.65	67.05
China	Eastern Asia	89.35	94.80		66.45
Colombia	South America	97.76	94.20	77.47	62.70
Comoros	Eastern Africa	81.74	84.40	50.36	37.85
Congo, Dem. Rep.	Middle Africa	36.80	78.30	18.31	33.13
Congo, Rep.	Middle Africa	89.29	96.55		50.59
Costa Rica	Central America	97.41	95.65	82.45	62.76
Cote d'Ivoire	Western Africa	93.69	76.80	40.20	28.53
Croatia	Southern Europe	97.99		92.39	
Cuba	Caribbean	97.84		84.18	
Cyprus	Western Asia	97.78		95.34	
Czech Republic	Eastern Europe	89.36		90.52	
Denmark	Northern Europe	98.86		90.92	

Country	ILO Sub Region	ISCED 1 World Bank Net Adjusted Enrolment[55]	UNICEF Net Adjusted Attendance[57]	ISCED 2 & 3 World Bank Net Enrolment[56]	UNICEF Net Adjusted Attendance[57]
Djibouti	Eastern Africa	67.03	69.50	37.82	
Dominica	Caribbean	97.98		87.74	
Dominican Republic	Caribbean	93.87	95.20	70.61	63.05
Ecuador	South America	97.58	95.40	84.67	77.15
Egypt, Arab Rep.	Northern Africa	98.46	96.80	82.78	77.20
El Salvador	Central America	81.60	95.80	61.83	57.40
Equatorial Guinea	Middle Africa	44.35		20.36	
Eritrea	Eastern Africa	51.83	81.00	41.58	59.10
Estonia	Northern Europe	93.93		94.36	
Eswatini	Southern Africa	82.59	97.70	41.70	
Ethiopia	Eastern Africa	85.20	68.18	30.81	17.57
Fiji	Western Pacific Islands	99.44		84.52	
Finland	Northern Europe	98.69		96.10	
France	Western Europe	99.47		94.67	
French Polynesia	Western Pacific Islands	99.39			
Gabon	Middle Africa	90.91	97.70		35.35
Gambia, The	Western Africa	81.81	78.10		8.22
Georgia	Western Asia	99.21	97.90	95.95	90.30
Germany	Western Europe	90.35		85.30	
Ghana	Western Africa	86.70	80.94	57.24	30.28
Gibraltar		99.70		93.84	22.32
Greece	Southern Europe	98.22		93.35	
Grenada	Caribbean	99.24		87.73	
Guatemala	Central America	89.21	93.60	43.78	41.60
Guinea	Western Africa	78.09	66.13	32.21	37.45
Guinea-Bissau	Western Africa	72.67	68.68	8.56	
Guyana	South America	97.28	97.00	82.34	80.55
Haiti	Caribbean	58.11	84.24		24.82
Honduras	Central America	80.47	90.72	43.78	40.54
Hong Kong SAR, China	Eastern Asia	96.27		96.14	
Hungary	Eastern Europe	96.51		89.28	
Iceland	Northern Europe	99.92		91.27	
India	Southern Asia	97.74	95.20	61.63	72.20
Indonesia	South-eastern Asia	94.38	99.40	78.73	72.15
Iran, Islamic Rep.	Southern Asia	99.77	96.68	81.38	
Iraq	Western Asia	93.00	91.60	45.16	45.30
Ireland	Northern Europe	99.88		98.66	
Israel	Western Asia	97.32		98.64	
Italy	Southern Europe	97.24		94.66	
Jamaica	Caribbean	81.38	98.00	73.97	83.95
Japan	Eastern Asia				
Jordan	Western Asia	80.95	97.36	62.60	79.92
Kazakhstan	Central Asia	98.77	99.50	99.84	97.50
Kenya	Eastern Africa	81.23	85.45	47.42	38.85
Kiribati	Western Pacific Islands	96.09	95.99	69.13	67.58
Korea, Dem. People’s Rep.	Eastern Asia	97.75	96.70		95.45
Korea, Rep.	Eastern Asia	97.55		98.01	
Kosovo					
Kuwait	Western Asia	88.24		86.53	
Kyrgyz Republic	Central Asia	98.67	98.70	84.39	91.80
Lao PDR	South-eastern Asia	91.47	89.60	60.01	49.30
Latvia	Northern Europe	97.11		93.80	
Lebanon	Western Asia	97.87			
Lesotho	Southern Africa	91.20	96.60	41.35	38.45
Liberia	Western Africa	44.57	42.69	15.69	12.80
Libya	Northern Africa	98.06			
Liechtenstein	Western Europe	99.31		85.94	

Country	ILO Sub Region	ISCED 1 World Bank Net Adjusted Enrolment[55]	UNICEF Net Adjusted Attendance[57]	ISCED 2 & 3 World Bank Net Enrolment[56]	UNICEF Net Adjusted Attendance[57]
Lithuania	Northern Europe	99.60		98.43	
Luxembourg	Western Europe	98.36		83.58	
Macao SAR, China	Eastern Asia	96.42		86.42	
Madagascar	Eastern Africa	96.87	76.10	29.85	20.00
Malawi	Eastern Africa	98.23	93.70	34.24	22.70
Malaysia	South-eastern Asia	99.52		72.21	
Maldives	Southern Asia	95.43	94.80		59.30
Mali	Western Africa	58.94	53.10	29.93	25.40
Malta	Southern Europe	99.55		92.96	
Marshall Islands		74.53		55.85	
Mauritania	Western Africa	80.31	59.48	30.98	24.27
Mauritius	Eastern Africa	94.99		84.31	
Mexico	Central America	99.17	98.80	81.16	78.75
Micronesia, Fed. Sts.	Western Pacific Islands	85.46			
Moldova	Eastern Europe	89.79	98.70	77.96	81.95
Monaco	Western Europe				
Mongolia	Eastern Asia	98.69	96.10	81.89	89.75
Montenegro	Southern Europe	96.87	95.17	89.07	90.29
Morocco	Northern Africa	99.16		64.49	
Mozambique	Eastern Africa	93.93	71.50	19.28	9.60
Myanmar	South-eastern Asia	98.05	92.80	64.06	52.25
Namibia	Southern Africa	98.15	92.29	52.04	42.35
Nauru		93.96	97.30	71.81	
Nepal	Southern Asia	96.30	74.49	61.87	48.83
Netherlands	Western Europe	99.03		93.16	
New Zealand	Australia and New Zealand	99.18		92.28	
Nicaragua	Central America	96.32	100.00	48.42	39.65
Niger	Western Africa	66.49	50.40	20.07	11.60
Nigeria	Western Africa	65.98	66.70		
North Macedonia	Southern Europe	95.73	98.03	78.93	93.82
Norway	Northern Europe	99.88		95.61	
Oman	Western Asia	95.47	97.50	96.19	
Pakistan	Southern Asia	68.19	61.93	37.40	32.89
Palau	Western Pacific Islands	95.25			
Panama	Central America	86.78	97.10	63.79	72.00
Papua New Guinea	Western Pacific Islands	75.55		32.38	
Paraguay	South America	87.84	98.40	65.88	71.20
Peru	South America	98.50	91.90	89.31	75.85
Philippines	South-eastern Asia	95.03	94.33	65.56	57.56
Poland	Eastern Europe	97.16		94.08	
Portugal	Southern Europe	97.71		94.66	
Puerto Rico	Caribbean	78.79		75.92	
Qatar	Western Asia	98.19	96.41	93.89	90.54
Romania	Eastern Europe	85.71	91.57	82.85	90.04
Russian Federation	Eastern Europe	97.84		90.68	
Rwanda	Eastern Africa	95.28	94.40	35.87	22.20
Samoa	Western Pacific Islands	95.75		85.52	
San Marino	Southern Europe	93.89		66.54	
Sao Tome and Principe	Middle Africa	93.97	94.10	65.23	35.85
Saudi Arabia	Western Asia	95.11		96.36	
Senegal	Western Africa	76.46	61.02	37.67	24.17
Serbia	Southern Europe	98.22	98.80	92.07	94.25
Seychelles	Eastern Africa	92.86		80.06	
Sierra Leone	Western Africa	98.97	81.80	41.77	32.40
Singapore	South-eastern Asia	99.97		99.78	

Country	ILO Sub Region	ISCED 1 World Bank Net Adjusted Enrolment[55]	UNICEF Net Adjusted Attendance[57]	ISCED 2 & 3 World Bank Net Enrolment[56]	UNICEF Net Adjusted Attendance[57]
Sint Maarten (Dutch part)				69.76	
Slovak Republic	Eastern Europe	83.15		84.76	
Slovenia	Southern Europe	98.31		95.69	
Solomon Islands	Western Pacific Islands	67.47	66.00	30.99	
Somalia	Eastern Africa				
South Africa	Southern Africa	92.45	98.46	71.93	77.46
South Sudan	Eastern Africa	35.25	23.49	5.48	4.60
Spain	Southern Europe	97.34		96.88	
Sri Lanka	Southern Asia	99.27	95.71	91.04	82.55
St. Kitts and Nevis		96.22		98.00	
St. Lucia	Caribbean	98.29	99.51	81.31	88.40
St. Vincent and the Grenadines	Caribbean	98.49		89.47	
Sudan	Northern Africa	61.70	68.10	31.50	30.15
Suriname	South America	86.03	96.60	57.79	46.45
Sweden	Northern Europe	99.42		99.06	
Switzerland	Western Europe	99.62		85.33	
Syrian Arab Republic	Western Asia	72.25		48.50	
Tajikistan	Central Asia	99.10	97.66	83.22	88.81
Tanzania	Eastern Africa	82.35	80.80	26.55	15.40
Thailand	South-eastern Asia	98.08	95.55	77.27	78.16
Timor-Leste	South-eastern Asia	95.41	89.82	62.74	45.93
Togo	Western Africa	94.69	91.21	41.01	38.41
Tonga	Western Pacific Islands	98.88	97.03	82.07	72.59
Trinidad and Tobago	Caribbean	98.78		72.65	
Tunisia	Northern Africa	98.84	96.90	32.37	70.65
Turkey	Western Asia	94.88	95.44	87.23	
Turkmenistan	Central Asia		98.10		96.65
Tuvalu	Western Pacific Islands	87.89		66.73	
Uganda	Eastern Africa	95.64	84.80	22.37	13.60
Ukraine	Eastern Europe	91.99	99.80	85.68	81.60
United Arab Emirates	Western Asia	98.74		92.80	
United Kingdom	Northern Europe	99.57		97.13	
United States	Northern America	95.56		92.45	
Uruguay	South America	99.64	97.12	88.21	59.20
Uzbekistan	Central Asia	96.84		90.86	
Vanuatu	Western Pacific Islands	92.15	77.20	48.94	
Venezuela, RB	South America	89.68		73.24	
Vietnam	South-eastern Asia	100.00	97.73	35.77	80.55
West Bank and Gaza	Western Asia	97.11		87.23	
Yemen, Rep.	Western Asia	84.40	76.42	47.59	
Zambia	Eastern Africa	85.10	84.10		
Zimbabwe	Eastern Africa	94.63	90.60	48.73	

To calculate daily schooling hours, the enrolment rates associated with each age were multiplied by a daily instruction time. Weekly compulsory instruction time was obtained for ISCED 1 and ISCED 2 from the most recent year for all OECD countries [58] and converted to daily instruction hours averaged over the full year. Weekly compulsory instruction time is defined as the instruction time a public school is expected to provide to students based on the compulsory curriculum, and does not include breaks between classes, homework time, tutoring, studying, holidays, or examinations. Because instructional time was not available for non-OECD countries or ISCED 3, we used the average across OECD countries of 2.36 hours per day per student and assumed the same instructional time per day for students enrolled in ISCED 3. The instructional time was multiplied by the country-specific enrolment rates for each 1-year age bin to estimate the daily schooling hours.

4.2 Youth Employment time

Working rates were transcribed from the *ILO Global Estimates of Child Labour* report. These data were collected from 105 national household surveys covering more than 70 per cent of the world population of children aged 5 to 17 years [59]. The specific indicator used to capture global working rates is “children in employment”, which includes children working in both formal and informal work, i.e. in market production as well as non-market production (e.g. for own-use agricultural products). This indicator includes children employed legally in light and non-hazardous work, as well as work done under the subcategory “child labour”.

The “children in employment” rate for children ages 5-17 was obtained for each of the 5 ILO regions: Africa, Americas, Asia and the Pacific, Europe and Central Asia, and Arab States. In order to align with the general ILO economic activity data, we multiplied these rates by the fraction 10/12 to estimate the fraction applicable to ages 5-15. Data on the average working hours of children ages 7-14 not attending school were downloaded from the World Bank in the units of hours per week [60]. The daily work hours were averaged across each ILO sub region and applied to all ages 5-15. No working hour data were available for OECD countries because youth working rates are considered small in these countries.

4.3 Fixed and Proportional Activities

The daily activities of youth outside of education and employment were estimated from published time use surveys (Table S5). A relatively small number of time use surveys are available that report on children [61], among which we used only those with full 24-hour coverage and well-described methodology, leaving a total of 9 studies. Taken together, these surveys include youth from birth to age 18. It should be noted that the studies represent a small number of countries, most of which are relatively wealthy, leading to large potential biases that could be addressed with future work.

Table S5 – Characteristics of the time use surveys used in the youth model.

Country	Year	Data Collection Method	Number of Respondents	Age Range	Source
Australia	2004	2 24hr diaries	4983	4-5	[62]
Australia	2007	4-day recall: 2 in-person and 2 phone interviews	1853	9-16	[63]
Belgium	1999	2 24hr diaries	750	12-19	[64]
Canada	2001-2003	24hr diary	2154	19-19	[65]
Czechia	1992	24hr diary	257	13-18	[66]
Indonesia	2007	24hr diary	2928	9-18	[67]
New Zealand	2008	4-day recall: 2 in-person and 2 phone interviews	679	10-16	[68]
United States of America	1997	24hr diary and interview	3536	0-12	[69]
South Africa	2001	Recall interview	3923	10-20	[70]

The activities reported within each survey were associated with MOOGAL subcategories over the study-relevant age range, and the time use summed by age (see section 6). We compared the time use surveys to identify subcategories that did not change substantially across countries. Meals, hygiene & grooming, and human transport showed little variation, with <15 minutes per day difference between surveys for a given age. Because of the sparse data coverage, we assumed that the average for each of these activities, at a given age, was globally-representative of the 'fixed' daily activities of youth.

Sleep time has been frequently measured for youth in dedicated sleep studies, and we were therefore able to use these to supplement our constraints on how sleep varies with age. Sleep data were collected from reports by ref. [71] for nearly 70 000 children between the ages 0-12 in 18 countries. For ages 13-18, sleep time was collected through actigraphy, including 79 studies and involving children from 17 countries. These data were averaged by age to estimate the sleep hours at each age, also included as a fixed activity.

After accounting for country-specific schooling and employment, as well as age-dependent fixed activities, the remaining time in the youth model was apportioned among the remaining subcategories, which we refer to as proportional activities. We calculated the time spent on each proportional activity for each 1-year age bin from the available time use studies, and these proportional subcategory weightings were applied to occupy the remaining time for each 1-year age bin, for each country.

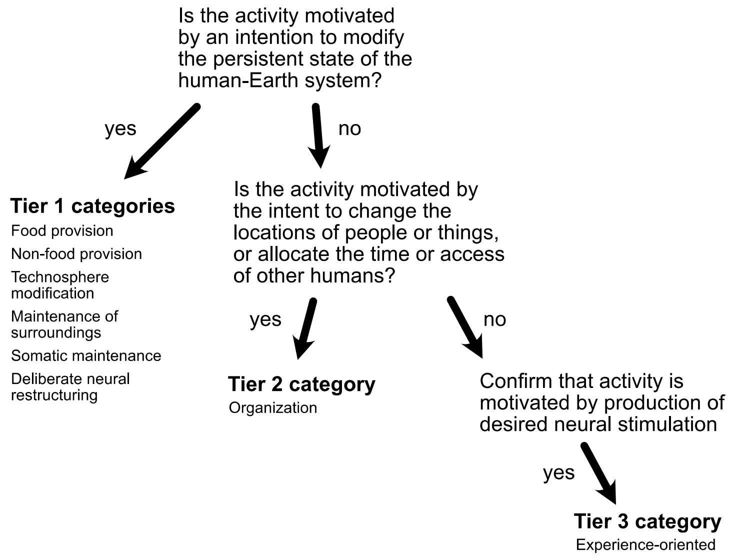
5 Standardising Activity Classifications: MOOGAL

Given the diversity of our data sources, it was necessary to cross-map across a large number of activity categorization systems, known as lexicons. Activities can be classified in different ways, according to the intended purpose of the classification system (see ref. [72] for discussion). For example, the number of activities included in the TUS classifications range from 8 to over 150 (see Table S1), and there is little to no overlap between sociological and economic lexicons given that they focus on different aspects of human life. To combine the activities, we use a common lexicon within which our data sources are redefined. The lexicon and its application are described in detail by ref. [72], of which we provide a few key aspects here.

5.1 Motivating Outcome-Oriented General Activity Lexicon

The Motivated Outcome-Oriented General Activity Lexicon (MOOGAL) is a hierarchically structured lexicon divided into 8 categories and 24 subcategories. Subcategories are defined based on the identifiable physical outcomes that motivate the undertaking of an activity, rather than other features such as social motivations (e.g., whether or not the activity is done for pay) or the contextual features in which the activity occurs (e.g., watching television). The functional application of the MOOGAL to the various activity classifications is made at the subcategory level; by using a consistent theoretical orientation, the MOOGAL subcategories can be more readily associated to different lexicons while maintaining exclusivity. A 3-tier priority scheme is used to mitigate arbitrariness for compound activities that have multiple outcomes (Fig. S6). We use the term “activity” to refer to the individual items that compose the given time use, economic, or youth data classification scheme.

Figure S6. Priority flowchart for associating activities with Tier 1, Tier 2 or Tier 3 categories.



5.2 MOOGAL Association Method

Each unique activity classification of length *n* was converted to the MOOGAL by fractionally associating the time in each individual activity with one or more of the subcategories in an $n \times 24$ concordance matrix. We refer to these fractions as "time fractions." When an activity is associated uniquely to a single subcategory the time fraction is 1.0, meaning the entire amount of time allocated to the given activity maps directly to the one sub-category. In some cases, an activity is clearly an umbrella term that aggregates multiple component activities. In other words, the reported activity is composed of smaller activities with different motivating outcomes, according to the MOOGAL sub-categories (e.g., 'housework' as reported in some surveys includes both 'maintenance of inhabited environment' and 'food preparation'). In such cases, the time fractions associated with the relevant subcategories are determined by focusing on the dominant or most-likely subcategory, entering a best-estimate of the fraction, and iterating through the remainder of subcategories until the original time has been fully recategorized. The fractions must sum to 1 to ensure the time in each activity is conserved.

Best-estimates of fractions are reached by cross-referencing with other activity classifications or consulting detailed coding methodologies for the survey lexicon. For example, "agriculture, forestry and fishing" of ISIC level 1 contains the M24 sub-categories of "food growth and collection", as well as "material provision" (lumber, cotton and other fibre crops). In this case the fractions are chosen by comparing this to ISIC level 2 employment data, where agriculture is explicitly differentiated from forestry, and estimating the fraction of agricultural labour that is in cotton and fibre crops from ancillary data sources.

All concordance matrices are provided, for each TUS and economic dataset, in the online data supplement.

6 Uncertainty Assessment

Although uncertainty assessments are not typically provided with time use data, we aim to generate a first order estimate of the uncertainties in the final results, in order to help with their interpretation. To do so we undertook an uncertainty assessment that includes four main components: a baseline uncertainty that arises from the degree to which the original datasets describe mean annual time allocation across the population, uncertainty in the MOOGAL association of activities between lexicons, uncertainty arising from interpolation to countries missing data, and uncertainty in the youth model. The baseline uncertainty is a uniform relative value for a given data source, whereas the other three components vary by subcategory. Our assessment is admittedly coarse. The stated uncertainties are intended to be semi-qualitative, rather than a thorough quantifications of error. We also emphasize that this assessment was not able to include all sources of uncertainty, such as those related to recall bias by survey respondents or the initial coding and aggregation of activities by national statistics agencies. The uncertainty assessment is intended as a first step towards a more formal treatment of uncertainty in time use statistics that can be improved with further work.

6.1 Baseline Uncertainty (σ_{base})

Each of our initial data sources has an inherent uncertainty, which we refer to as the baseline uncertainty. Unfortunately, this is generally not estimated by the data providers, so we have attempted to provide an approximation using a transparent scheme that assigns different uncertainties based on objective characteristics of the data. The American Time Use Survey is notable in providing an estimate of variances using a replicate variance method. The standard errors generated by this method vary by activity and range from 0.3% to 6.9%. Based on this assessment, we assume a variance of 5% for a high-quality TUS. We then graded the robustness of each time use survey to reflect disparities in survey methodology and design across countries.

Quality levels were assessed based on survey duration, data collection method, and lexicon length, following the rubric in Table S6. Surveys with a combined score of 4/4 were graded as “A”, corresponding to a background uncertainty of 5%. Surveys scoring 2/4 or 3/4 were graded as “B”, corresponding to a background uncertainty of 10%. Surveys with 1/4 or less were graded “C”, corresponding to a background uncertainty of 20%. A low-scoring assessment does not necessarily imply a low-quality survey, as it could also reflect a lack of methodological detail in the available survey description.

For economic data, we only consider uncertainty due to inconsistency in the labour force coverage. The relative baseline uncertainty is taken to be the difference between the fraction of the labor force covered and the reported full labor force size, or: |1 – *fraction*|. For the youth model, we introduce a baseline uncertainty of 25%, as the uncertainties on the youth time use surveys can be considered to be larger than those on the general population time use surveys.

Table S6. Rubric for assigning quality score to time use surveys.

Characteristic	**2 points**	**1 point**	**0 points**
Survey duration	1 year	2-11 months	<2 months
Data collection method	N/A	Diary and/or interview	Unknown method
Lexicon length	N/A	15+ activities	<15 activities

6.2 Uncertainty from MOOGAL Associations (σ_{M24})

The fractional allocation of time in a given activity to two or more subcategories inevitably introduces uncertainty (see section *6.2*). We account for the uncertainty in converting activity classifications to the MOOGAL by estimating the feasible upper and lower bounds on the largest time fraction for each activity-subcategory pair. This range is approximate but is intended to represent the best-estimate equivalent of a ≈95% confidence range, which we equate to 2σ. The process is then repeated for the remaining fractions in descending order. When an activity maps to a single MOOGAL subcategory, the fraction is 1.0 and the associated uncertainty on the fraction is 0. When an activity maps to two subcategories, the fractions allocated to each subcategory (that together sum to 1) are assigned uncertainty bounds under the condition that the sum of the lower bound of first, and the upper bound of the second (or vice-versa), must sum to 1. When an activity maps to three or more subcategories, maintaining the condition that a combination of upper and lower bounds must sum to 1 becomes impractical. We therefore take the pragmatic step of assigning the uncertainty bounds to the largest fraction first and working in diminishing order. All associations were estimated indepependently by at least 3 coders, and the largest uncertainties were used.

6.3 Uncertainty from Interpolations (σ_{interp})

We interpolated both TUS and economic activity data to countries missing data. We grouped the world into 17 regions based on the World Bank subregion grouping. For each region, we filled missing countries with the population-weighted mean time per subcategory. The region standard deviation was taken as the uncertainty on the interpolated values. Four regions had only one country with a time use survey (middle Africa, southern Africa, central Asia, and south-eastern Asia). For these regions, the interpolated uncertainty is defined as the sum of twice the global variance and the variance for the single available country.

6.4 Youth Uncertainty (σ_{youth})

The uncertainty for the youth model was calculated from two components: the enrolment rate and the instructional time. The enrolment rate uncertainty for each country with enrolment rate data was estimated by taking the standard deviation of the World Bank net adjusted enrolment and UNICEF net adjusted attendance. For each region, uncertainty on missing countries was filled in using the mean uncertainty. Uncertainty in the average instructional time was estimated for each region by taking the standard deviation of instructional time among all OECD countries, as these are the only countries with instructional time data. These two uncertainties were added in quadrature to provide an overall uncertainty on the mean youth instructional time by ILO region.

7 Merging Economic and Time Use Survey Data

We combine the TUS and economic data sources using the constraint that, for any population, the sum of subcategories must equal 24 hours. Before outlining our method for combining TUS with economic activity data, a careful consideration of both the System of National Accounts (SNA) and the definition of employment is required.

7.1 Definition of employment

The System of National Accounts (SNA) [73] framework underlies the structure of all work activities in both TUS and LFS. It needs to be considered in order to avoid inconsistencies in the integration of labour force and time use survey data. The SNA identifies five forms of work that fall within the production boundary: work for pay or profit, unpaid trainee work, non-compulsory unpaid volunteer work, household production of goods for own final use, and other work activities. Own-use production of goods includes activities such as household agricultural production, gathering of firewood, construction of dwellings, and making clothing and other items. Critically, own-use service activities are excluded from the SNA, meaning activities such as preparing meals, caring for children and other household members, cleaning, household repairs, and transporting members of the household are not considered work within the SNA production boundary [73].

In industrialized and higher-income countries the distinction between work for pay or profit and own-use production is usually a clear distinction, with a vast majority of work happening in the context of the formal economy (i.e., market wage labour). However, the boundary between formal economic and informal or subsistence work is often poorly defined in lower-income countries with significant rural, agrarian populations. Determining the degree to which an individual or household is subsistent is difficult given that there is no single, clear boundary separating small-holder, family, and subsistence farming [74]. We therefore do not attempt to draw these distinctions but rely on the ILO definition of employment.

The ILO's 13th International Conference of Labour Statisticians (ICLS) defined a person as employed if they engaged in one of the five forms of SNA work for at least one hour during the reference period, often one week or one month [75]. This means that individuals who work solely in household production of goods for own use are considered employed and are therefore counted as members of the labour force. Individuals providing household services for own use are not counted as employed or economically active and are therefore not counted in the labour force. For example, an individual farmer who allocates some of their working time to producing market-bound outputs and the rest to subsistence is counted in a labour force survey as employed. Meanwhile, an individual who is occupied with home keeping and caring for household members is not employed and is excluded from the labour force [75].

Subsequently, the 19th ICLS changed the definition of employment, narrowing it to include only those working for pay or profit; those working in own-use production of goods are no longer considered employed or part of the labour force [75]. However, ILOSTAT identifies the LFS data used here as adhering to the previous (13th ICLS) definition of employment. To avoid inconsistencies, we therefore based our methods for integrating the economic data with the time use surveys on the 13th ICLS definition of employment.

7.2 Combining TUS and Economic Data

TUS record the time spent working in the formal economy, but do not resolve the specific activities. Rather, working time is often included as a single aggregated activity (e.g., "paid work" or "employment" in most industrialized countries) or as a set of the five forms of SNA work (e.g., "paid work", "household primary production", etc., in many lower-income countries). Since household producers of goods for own final use are counted in the economic data according to the 13th ICLS definition, all SNA work activities are coded as a supplemental category, *work for employment*, rather than as one of the MOOGAL subcategories. The economic LFS data are meanwhile coded to the appropriate MOOGAL subcategories. The population-average time in each subcategory from the economic activity data then replaces the *work for employment* TUS subcategory.

Prior work has shown that time use surveys provide a more accurate measure of total work time than labour force surveys [76],[74],[77]. Therefore, the TUS *work for employment* time is assumed to correctly capture the total population-average working time for each country, and the economic activity data is used to determine the distribution of this time among subcategories. Theoretically, population-average time in *work for employment* should match the sum of population-average time in the economic activity subcategories. However, it does not precisely match because the two measures are collected separately using different methodologies. Where there is a mismatch, we scale the population-average time in the economic activity subcategories proportionally such that their sum equals the population-average time in *work for employment.*

7.3 Combining Uncertainties

We sequentially combine the four sources of uncertainty separately for each subcategory to compute the uncertainty on the global mean. The following steps describe how this is achieved for a single subcategory.

1. σ_{TUS}^2 and σ_{econ}^2 are calculated using σ_{M24} and σ_{base}. σ_{M24} is defined by the concordance matrix and is of dimension (n_{TUS} x n_{M24}) or (n_{econ} x n_{M24}). We square σ_{M24} and σ_{base} to obtain the variances and multiply each variance by the square of the vector *t*, which is comprised of the time in the subset of activities $i=1 \ldots m$ that map to the subcategory in the concordance matrix.

$$(1.1) \quad \sigma_{TUS}^2 = \sum_{i=1}^{m} \sigma_{M24,i}^2 * t_i^2 + \sigma_{base}^2 * t_i^2$$

$$(1.2) \quad \sigma_{econ}^2 = \sum_{i=1}^{m} \sigma_{M24,i}^2 * t_i^2 + \sigma_{base}^2 * t_i^2$$

   σ_{M24} and σ_{base} are uncorrelated because the estimated uncertainties on each MOOGAL time fraction (*i.e.*, the upper and lower bounds) are generated independently from the baseline uncertainty (see Table S6).

2. For the youth model, σ_{youth}^2 is calculated from the sum of variance σ_Y^2 on time *t* for each age, over ages $y=0 \ldots Y_{min}$, and σ_{base}^2.

$$(2.1) \quad {\sigma_{youth}}^2 = \sum_{y=0}^{Y\min} \sigma_Y^2 * t_Y^2 + \sigma_{base}^2 * t_Y^2$$

   The activity from the youth model is then added to that from the time use surveys using population weights. The variance in the youth model, σ_{youth}^2, is combined with σ_{TUS}^2 to produce σ_T^2, the variance on the whole-population mean.

$$(2.2) \quad \sigma_T^2 = \sigma_{youth}^2 * \left(\frac{pop_{youth}}{pop_{total}}\right)^2 + \sigma_{TUS}^2 * \left(\frac{pop_{adult}}{pop_{total}}\right)^2$$

   Both σ_{youth}^2 and σ_{TUS}^2 are assumed to be uncorrelated as the youth model is generated independently from the time use survey data.

3. For each region, for both TUS and economic data, we interpolate missing countries. If the region has 4 or more countries, the variance introduced from the interpolations, σ_{interp}^2, is taken to be the square of the regional standard deviation. For regions with 3 or fewer

countries, σ_{interp}^2 is calculated as the sum of the maximum country variance and twice the global standard deviation, squared.

4. Next, the TUS and employment time are merged. The variances σ_T^2 and σ_{econ}^2 are summed along with an uncertainty derived from the scaling of the employment time E to match the TUS work employment time:

$$(4.1) \quad {\sigma_{merged}}^2 = (E^2 * \left|1 - \frac{TUS_{work\ employment}}{\sum Employment\ time}\right|)^2 + \sigma_T^2 + \sigma_{econ}^2$$

   The uncertainties here are assumed to be uncorrelated as the numerator $TUS_{work\ employment}$ represents the supplemental MOOGAL subcategory (corresponding to the population-average employment time as measured by the TUS) and does not contribute to σ_{TUS}^2 (see section 7.2). It is also independent from the denominator, which is the population-average employment time as measured by the economic data.

5. Finally, the uncertainty on the global mean is calculated by weighting the variance σ_{merged}^2 by each country k's share of the total population:

$$(5.1) \quad \sigma_{global}^2 = \sum_{c=1}^{k} (\frac{pop_C}{pop_{world}})^2 * {\sigma_{merged}}^2$$

8 Regression analyses

We regressed country population-average time in each subcategory against country gross domestic product (GDP) per capita to test for correlation. We use ordinary least squares to regress the log base 10 of GDP in US dollars against the time in hours allocated to each subcategory. We use GDP per capita (PPP 2017 Int'l$) [78] as a proxy for material wealth and level of industrialization. The GDP per capita used was for the same year as the TUS where a TUS was available, otherwise it was for the same year as the economic data. To check for robustness to the interpolation of data, we recalculated the regressions for multiple subsets: (*i*) countries with observed TUS and economic data that is either observed or interpolated (*n=58)*; and (*ii*) countries with observed economic data and TUS data that is either observed or interpolated (*n=139)*. We also show results for only countries where both sources of data are observed (i.e. no interpolations, *n=52*, Table S7 column 3).

In the main text we use group (*i*) for subcategories where the TUS (non-economic) activities form the predominant share of population-average time, and group (*ii*) for subcategories where the economic activities form the predominant share of population-average time. In order to test the robustness of our regression results to both the youth model and the inclusion of time use surveys with low activity resolution (and therefore a high relative uncertainty), we show additional results for subsets in which we removed the youth component and any countries with a relative uncertainty greater than 50% for the given subcategory. The results are summarized in Tables S7 and S8.

Table S7. P-values for linear regression of time versus log GDP per capita, by subcategory, for 6 data subsets including youth. Bold values in the Reference column refer to results for regressions used in Fig. 3 in the main text.

Subcategory	Reference	Both observed	*i.* TUS observed	*ii.* Economic observed	Both observed, <50% relative uncertainty	TUS observed, <50% relative uncertainty	Economic observed, <50% relative uncertainty
Meals	**.20**	.37	.20	.49	.11	.03*	.13
Passive	**p<.001*****	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***
Interactive	**.46**	.35	.46	.99	.22	.37	.11
Social	**.01***	.01*	.01*	p<.001***	.01*	.02*	p<.001***
Active	**p<.001*****	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***
Sleep	.05	.08	.05	.27	.07	.05	.14
Health Care	.09	.17	.09	.42	p<.001***	p<.001***	.53
Hygiene & Grooming	**.35**	.13	.35	.01*	.61	.86	.01*
Physical Childcare	.87	.84	.87	.69	.93	.97	.61
Religious Practice	p<.001***	p<.001***	p<.001***	.03*	p<.001***	p<.001***	p<.001***
Schooling & Research	p<.001***	.01*	p<.001***	p<.001***	.01*	p<.001***	p<.001***
Inhabited Environment	.05	.06	.05	p<.001***	.11	.08	p<.001***
Waste Management	p<.001***	.03*	.02*	p<.001***	.15	.15	.02*
Food Preparation	**.19**	.25	.19	.02*	p<.001***	p<.001***	.15
Food Processing	.03	.01*	.03*	p<.001***	.29	.29	.31
Food Growth & Collection	**p<.001*****	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***
Buildings	p<.001***	.05	.03*	p<.001***	.21	.08	p<.001***

Subcategory	Reference	Both observed	*i.* TUS observed	*ii.* Economic observed	Both observed, <50% relative uncertainty	TUS observed, <50% relative uncertainty	Economic observed, <50% relative uncertainty
Infrastructure	**p<.001*** **	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***
Artifacts	p<.001***	.08	.05	p<.001***	.13	.08	p<.001***
Materials	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***
Energy	.27	.65	.46	.27	.52	.46	.41
Material Transportation	.05	.43	.76	.05	.37	.93	.59
Human Transportation	**.43**	.22	.43	.91	.05	.17	.63
Allocation	**p<.001*** **	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***

Table S8. P-values for linear regression of time versus log GDP per capita, by subcategory, for 6 data subsets excluding youth. Bold values in the Reference column refer to results for regressions used in Fig. 3 in the main text.

Subcategory	Reference	Both observed, no youth	*i)* TUS observed, no youth	*ii)* Economic observed, no youth	Both observed, no youth, <50% relative uncertainty	TUS observed, no youth, <50% relative uncertainty	Economic observed, no youth, <50% relative uncertainty
Meals	**.20**	.32	.16	.31	.08	.02*	.07
Passive	**p<.001*** **	p<.001***	p<.001***	p<.001***	.01*	p<.001***	p<.001***
Interactive	**.46**	.01*	.01*	p<.001***	p<.001***	p<.001***	p<.001***
Social	**.01***	.01*	.01*	p<.001***	p<.001***	p<.001***	p<.001***
Active	**p<.001*** **	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***
Sleep	.05	.85	.99	.03*	.27	.25	.08
Health Care	.09	.39	.24	.14	p<.001***	p<.001***	.25
Hygiene & Grooming	**.35**	.25	.74	.07	.80	.47	.14
Physical Childcare	.87	.63	.59	.32	.75	.74	.25
Religious Practice	p<.001***	p<.001***	p<.001***	.01*	p<.001***	p<.001***	p<.001***
Schooling & Research	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***
Inhabited Environment	.05	.28	.36	.02*	.34	.37	.06
Waste Management	p<.001***	.09	.05	p<.001***	.27	.27	.03*

Subcategory	Reference	Both observed, no youth	*i)* TUS observed, no youth	*ii)* Economic observed, no youth	Both observed, no youth, <50% relative uncertainty	TUS observed, no youth, <50% relative uncertainty	Economic observed, no youth, <50% relative uncertainty
Food Preparation	**.19**	.05	.02*	.26	p<.001***	p<.001***	.99
Food Processing	.03	p<.001***	.01*	p<.001***	.11	.11	.34
Food Growth & Collection	**p<.001*** **	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***
Buildings	p<.001***	.10	.07	p<.001***	.23	.10	.03*
Infrastructure	**p<.001*** **	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***
Artifacts	p<.001***	.13	.13	p<.001***	.19	.19	.02*
Materials	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***
Energy	.27	.61	.37	.38	.50	.43	.43
Material Transportation	.05	.74	.75	.41	.30	.60	.40
Human Transportation	**.43**	.26	.55	.70	.10	.31	.94
Allocation	**p<.001*** **	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***	p<.001***

In all cases, and regardless of whether these time use components are included, we found that, food growth & collection, allocation, and infrastructure retain strong correlations to GDP per capita with p<.001, while human transportation is never significantly correlated to GDP per capita (p>.05). Meals is non-significant for nearly all iterations and is only weakly significant when highly uncertain countries are removed for a single data subset.

9 Sensitivity tests

As discussed in section 6, there is significant uncertainty in the data constraints. Some fractions of the global population, particularly youth, are not well-represented in the available data. In order to assess how the youth model influences our main result, the global human day, we recalculate the average time spent in all activities without accounting for the youth of age <Y_{min}, shown in Table S9. The results show that, without the youth model to account for this portion of the human population, the global human day includes less sleep, less passive and interactive experience, less active recreation, but more childcare, food provision, technosphere creation, maintenance of the inhabited environment, and allocation.

Table S9.

Subcategory	Reference	Youth model removed
Meals	1.60	1.64
Passive	2.59	2.48
Interactive	0.88	0.55
Social	1.12	1.15
Active	0.42	0.23
Sleep	9.10	8.72
Health Care	0.20	0.23
Hygiene & Grooming	1.05	1.04
Physical Childcare	0.29	0.34
Religious Practice	0.20	0.19
Schooling & Research	1.07	1.07
Inhabited Environment	0.75	0.85
Waste Management	0.01	0.01
Food Preparation	0.92	1.09
Food Processing	0.07	0.09
Food Growth & Collection	0.81	0.97
Buildings	0.22	0.26
Infrastructure	0.05	0.06
Artifacts	0.42	0.50
Materials	0.07	0.08
Energy	0.04	0.05
Material Transportation	0.31	0.37
Human Transportation	0.90	0.92
Allocation	0.91	1.10

To provide additional robustness checks we also recalculated the Global Human Day using the data subsets introduced in Section 8. The results are summarized in Tables S10 and S11.

Table S10. Global human day for 6 data subsets including youth. The ‘reference’ column refers to the values used in the main text and Figure 1.

Subcategory	Reference	Both observed	TUS observed	Economic observed	Both observed, <50% relative uncertainty	TUS observed, <50% relative uncertainty	Economic observed, <50% relative uncertainty
Meals	1.60	1.59	1.58	1.61	1.59	1.58	1.58
Passive	2.59	2.55	2.56	2.60	2.56	2.57	2.53
Interactive	0.88	0.86	0.87	0.85	0.86	0.87	0.89
Social	1.12	1.12	1.12	1.11	1.12	1.12	1.11
Active	0.42	0.44	0.44	0.42	0.43	0.43	0.42
Sleep	9.10	9.18	9.18	9.11	9.19	9.19	9.17
Health Care	0.20	0.17	0.17	0.19	0.16	0.16	0.17
Hygiene & Grooming	1.05	1.04	1.04	1.06	1.03	1.03	1.03
Physical Childcare	0.29	0.29	0.29	0.29	0.29	0.29	0.29
Religious Practice	0.20	0.19	0.19	0.19	0.18	0.19	0.20
Schooling & Research	1.07	1.02	1.03	1.05	1.02	1.03	1.05
Inhabited Environment	0.75	0.75	0.76	0.75	0.75	0.75	0.76
Waste Management	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Food Preparation	0.92	0.99	0.98	0.94	1.01	1.00	0.99
Food Processing	0.07	0.07	0.07	0.08	0.06	0.06	0.07
Food Growth & Collection	0.81	0.83	0.82	0.81	0.85	0.85	0.83
Buildings	0.22	0.21	0.21	0.23	0.21	0.21	0.21
Infrastructure	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Artifacts	0.42	0.44	0.44	0.42	0.45	0.45	0.43
Materials	0.07	0.06	0.06	0.07	0.07	0.07	0.08
Energy	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Material Transportation	0.31	0.31	0.31	0.32	0.32	0.32	0.32
Human Transportation	0.90	0.88	0.88	0.90	0.87	0.87	0.88
Allocation	0.91	0.90	0.90	0.91	0.90	0.90	0.90

Table S11. Global human day for 6 data subsets excluding youth. The ‘reference’ column refers to the values discussed in the main text and used in Fig. 1.

Subcategory	Reference	Both observed, no youth	TUS observed, no youth	Economic observed, no youth	Both observed, no youth, <50% relative uncertainty	TUS observed, no youth, <50% relative uncertainty	Economic observed, no youth, <50% relative uncertainty
Meals	1.60	1.64	1.63	1.65	1.63	1.63	1.62
Passive	2.59	2.44	2.45	2.50	2.46	2.47	2.40
Interactive	0.88	0.56	0.57	0.54	0.57	0.56	0.58
Social	1.12	1.11	1.11	1.13	1.12	1.12	1.19
Active	0.42	0.28	0.27	0.24	0.27	0.27	0.25
Sleep	9.10	8.88	8.88	8.76	8.92	8.91	8.85
Health Care	0.20	0.20	0.20	0.23	0.18	0.18	0.20
Hygiene & Grooming	1.05	1.03	1.03	1.05	1.02	1.01	1.02
Physical Childcare	0.29	0.33	0.33	0.34	0.33	0.33	0.34
Religious Practice	0.20	0.16	0.16	0.17	0.17	0.17	0.20
Schooling & Research	1.07	0.97	0.97	1.03	0.97	0.97	1.03
Inhabited Environment	0.75	0.83	0.84	0.84	0.82	0.83	0.86
Waste Management	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Food Preparation	0.92	1.16	1.15	1.11	1.17	1.17	1.17
Food Processing	0.07	0.09	0.09	0.09	0.08	0.08	0.08
Food Growth & Collection	0.81	1.00	0.99	0.96	1.04	1.04	0.98
Buildings	0.22	0.24	0.25	0.26	0.24	0.24	0.25
Infrastructure	0.05	0.07	0.06	0.06	0.06	0.06	0.06
Artifacts	0.42	0.54	0.54	0.51	0.54	0.54	0.52
Materials	0.07	0.07	0.07	0.08	0.09	0.09	0.09
Energy	0.04	0.05	0.05	0.05	0.05	0.05	0.05
Material Transportation	0.31	0.36	0.36	0.37	0.36	0.37	0.36
Human Transportation	0.90	0.90	0.89	0.92	0.89	0.89	0.89
Allocation	0.91	1.08	1.08	1.10	1.07	1.07	1.08

10 Additional Figures

Fig. S7. Histograms of time spent per activity subcategory, for each country, in hours per day averaged across the full population. Dark blue represents countries that include both economic data and time use surveys; pale blue represents only time use data; dark grey represents only economic data, and pale grey represents interpolated countries.

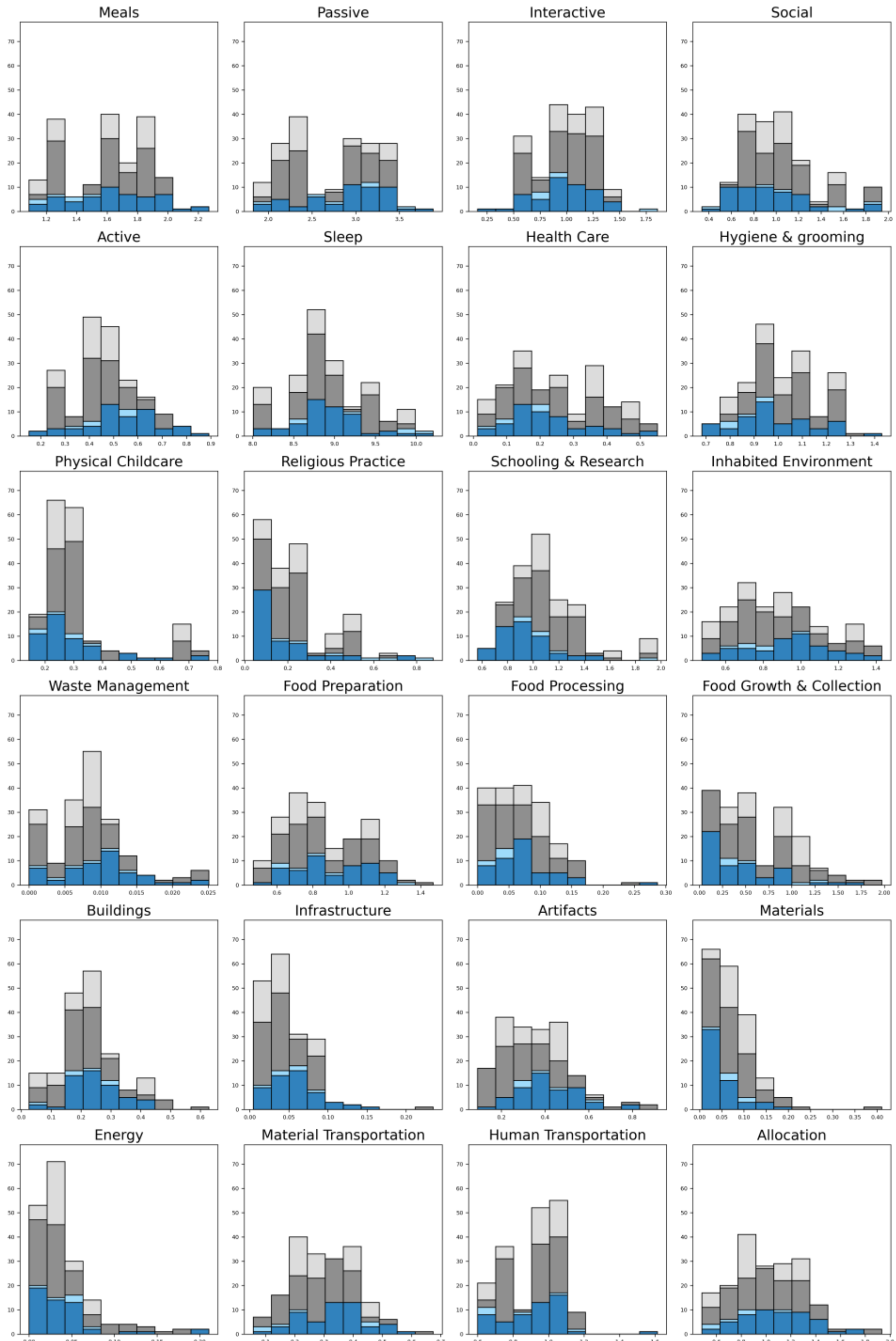


Fig. S8. Population-average time per subcategory, for countries with observed TUS.

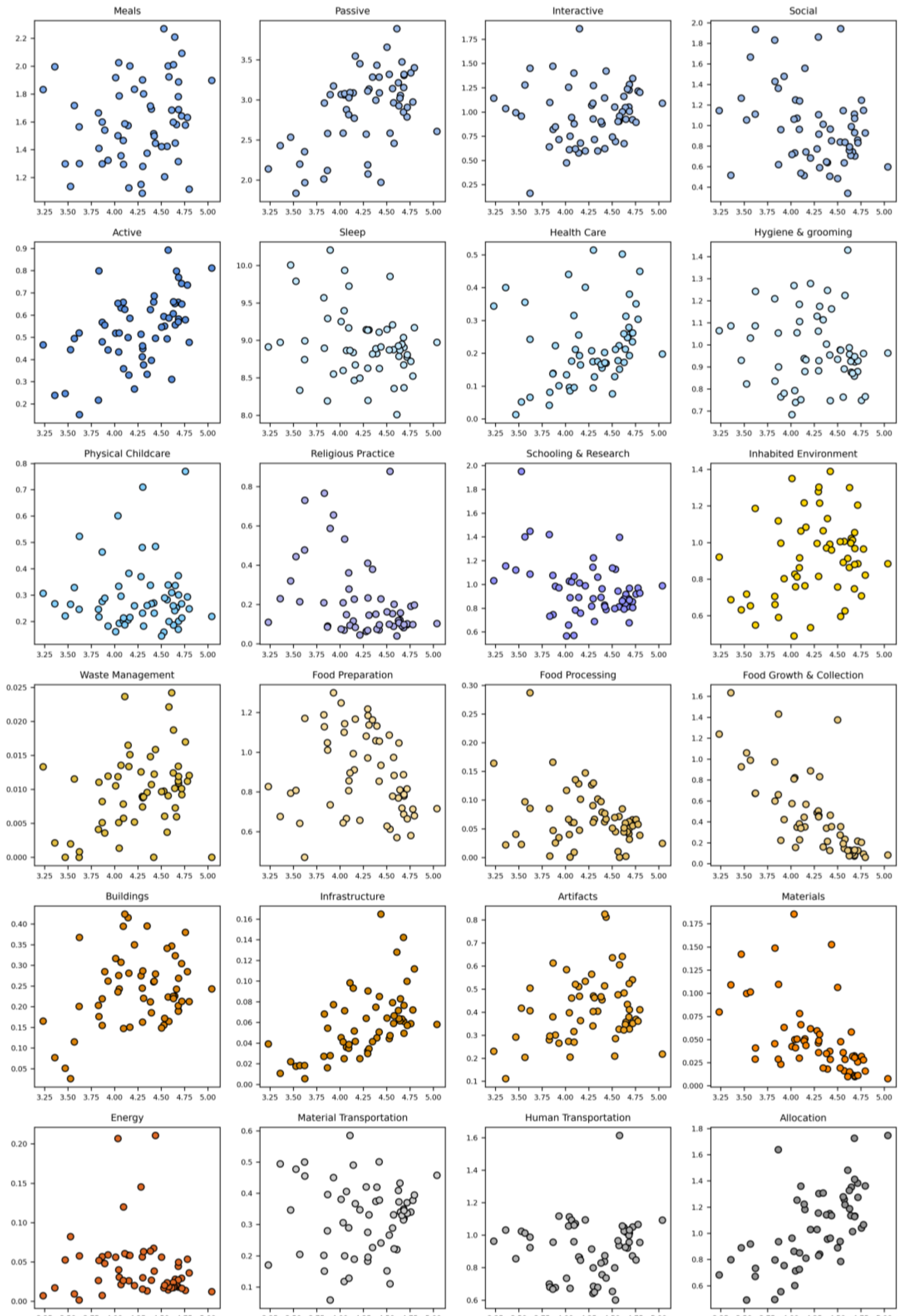
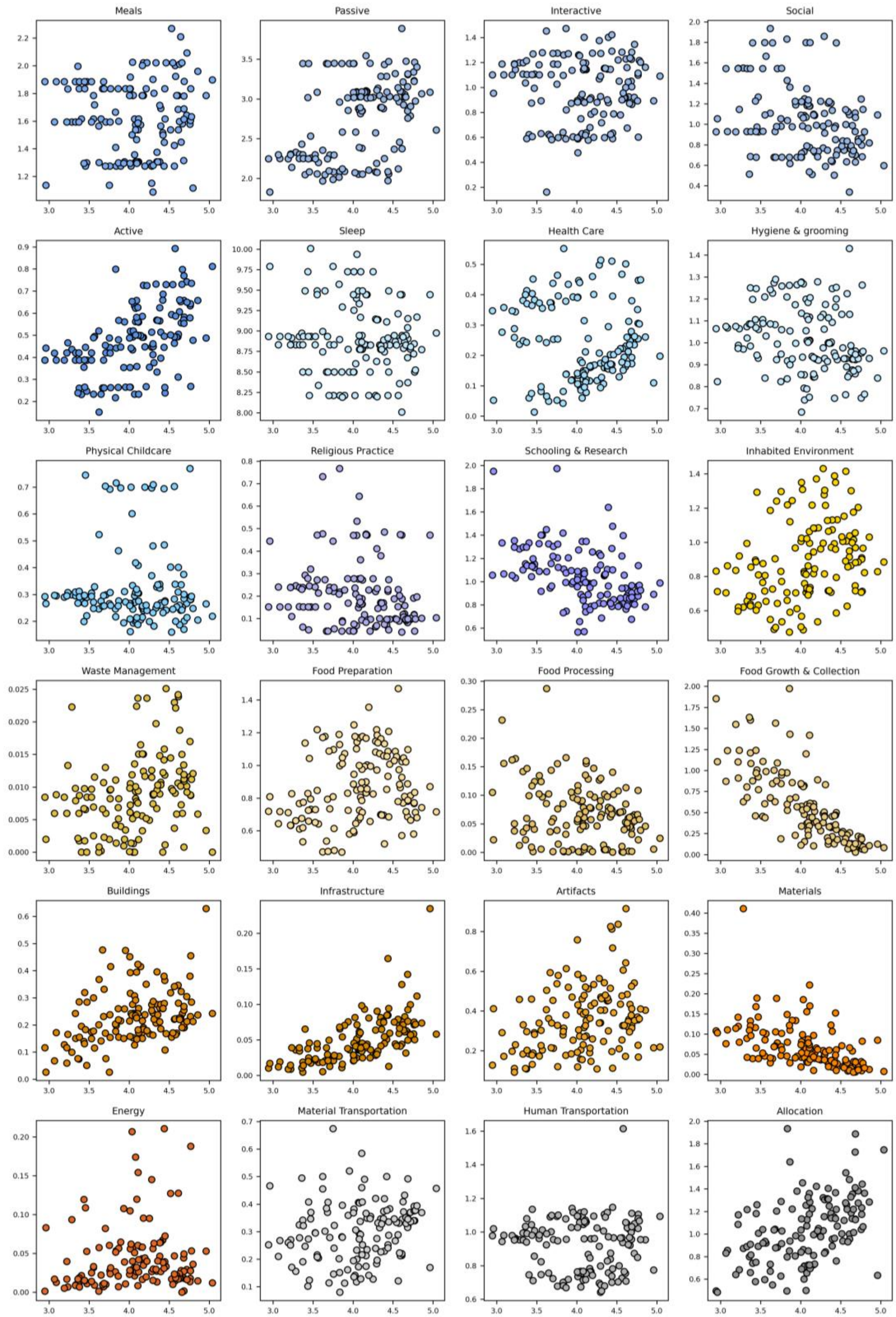


Fig. S9. Population-average time per subcategory, for countries with observed economic data.



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