



Health poverty among people with type 2 diabetes mellitus (T2DM) in Malaysia[☆]

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ABSTRACT

In the context of the escalating burden of diabetes in low and middle-income countries (LMICs), there is a pressing concern about the widening disparities in care and outcomes across socioeconomic groups. This paper estimates health poverty measures among individuals with type 2 diabetes mellitus (T2DM) in Malaysia. Using data from the National Diabetes Registry between 2009 and 2018, the study linked 932,855 people with T2DM aged 40–75 to death records. Cox proportional hazards models were used to estimate the 5-year survival probabilities for each patient, stratified by age and sex, while controlling for comorbidities and area-based indicators of socio-economic status (SES), such as district-level asset-based indices and night-time luminosity. Measures of health poverty, based on the Foster-Greer-Thorbecke (FGT) measures, were employed to capture excessive risk of premature mortality. Two poverty line thresholds were used, namely a 5% and 10% reduction in survival probability compared to age and sex-adjusted survival probability of the general population. Counterfactual simulations estimated the extent to which comorbidities contribute to health poverty. 43.5% of the sample experienced health poverty using the 5% threshold, and 8.9% were health poor using the 10% threshold. Comorbidities contribute 2.9% for males and 5.4% for females, at the 5% threshold. At the 10% threshold, they contribute 7.4% for males and 3.4% for females. If all patients lived in areas of highest night-light intensity, poverty would fall by 5.8% for males and 4.6% for females at the 5% threshold, and 4.1% for males and 0.8% for females at the 10% threshold. In Malaysia, there is a high incidence of health poverty among people with diabetes, and it is strongly associated with comorbidities and area-based measures of SES. Expanding the application of health poverty measurement, through a combination of clinical registries and open spatial data, can facilitate simulations for health poverty alleviation.

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1. Introduction

It is widely acknowledged both that health is an intrinsic aspect of an individual's wellbeing, and that poor health is strongly associated with deprivation. In the evaluation of societal deprivation, the consideration of health-based deprivation as a crucial dimension remains relatively unexplored. Despite mounting concerns over health disparities, and the extent to which they may reflect broader social injustices, work on the measurement of health poverty is in its infancy, especially compared to the extensive literature on income poverty (Atkinson, 1987; Allen, 2017; Ravallion, 2020). The need to move beyond a narrow focus on income poverty to broader wellbeing analysis calls for developing analytical tools for measuring health poverty, its distribution across groups and regions, and identifying which of its sources are amenable to cost-effective policy intervention.

Health poverty measures have recently been proposed to monitor deprivation in the domain of health (for example, the risk of early mortality), and its methodology is sufficiently flexible to be applied to a comprehensive set of clinical variables. The main concept behind health poverty is that individuals can be considered to be in 'poor health' if their health status is worse than a threshold that represents a minimally acceptable level of health (Clarke and Erreygers, 2020). This concept serves as a building block for quantifying and characterizing health poverty, while forging a path towards policy interventions that mitigate its impact. Using a health poverty approach in this study allows us to assess the disproportionate risk of premature mortality, while considering broad socioeconomic determinants (age, sex, asset index and luminosity) and comorbidities, which can shape the health of individuals with T2DM. Our choice of measurement (5-year survival) is relevant for studying a health condition like T2DM that significantly influences mortality. For people with T2DM, health poverty is not determined solely by having the disease, but also by its severity and relation with comorbidities. The latter provides a better understanding of the burden experienced by those affected by T2DM (which is associated to multimorbidity).

In the context of the escalating burden of diabetes within low and middle-income countries (LMICs), a pressing concern emerges regarding the widening of disparities in diabetes care and outcomes across different socioeconomic groups (NCD Risk Factor Collaboration (NCD-RisC), 2016). The prevalence of diabetes disproportionately impacts LMICs, which are home to approximately 80% of the global adult diabetes population (Flood et al., 2021). This escalating burden of diabetes affects life quality, contributes to excess mortality, and causes higher medical costs, an impact that is magnified in LMICs (Pradeepa et al., 2012). Asia is a major focal point of the escalating diabetes burden, as many of its countries are undergoing processes of socioeconomic transitions and urbanization that pose biological and environmental risk factors (Ramachandran et al., 2010; Pradeepa et al., 2012). Furthermore, Agarwal et al. (2023) mentions that social determinants of health like geographical disparity, structural racism, and ecological stress contribute to both an early onset of diabetes and higher diabetes rates among young individuals with lower body mass indexes in Asia, increasing the chances of enduring health complications through the life-course. Despite the substantial association between poverty and increased T2DM incidence, delayed diagnosis, inadequate care, and poor management (Hsu et al., 2012), studies underline the need for identifying local factors that impact marginalized populations within LMICs (Agarwal et al., 2023). Focusing our health poverty analysis on Malaysia is of particular relevance, given the country's sustained increases in prevalence of diabetes and raised blood glucose over the last decade, rising from 11.2% in 2011, to 13.4% in 2015 and 18.3% in 2019, with varying rates across different states (Institute for Public Health (IPH), National Institutes of Health, Ministry of Health Institute for Public Health Malaysia, 2020). In 2010, diabetes-related healthcare in Malaysia accounted for 16% of the country's overall national healthcare budget (Zhang et al., 2010).

This paper has two objectives. First, to measure the incidence, intensity and spatial distribution of health poverty, conceptualised as risk of early mortality, for people with type 2 diabetes mellitus (T2DM) in Malaysia. Second, to explore the explanatory factors of health poverty among people with T2DM, including comorbidities and indicators of socioeconomic status.

We use a rich data set including nearly 1 million people, aged 40–75, with diagnosed T2DM, linked with death records and merged with two area-based indicators of socioeconomic status (SES): a district-level asset index, and nighttime luminosity collected from satellite imagery. We estimate 5-year mortality using a Cox proportional hazards model, and measure health poverty through an adaptation of the Foster-Greer-Thorbecke family of poverty indices (Clarke and Erreygers, 2020).

The paper illustrates the utilization of large administrative data from Malaysia to focus on individuals at high mortality risk, by measuring health poverty and identifying key factors that contribute to health poverty. It is widely recognized both that health is an intrinsic aspect of an individual's well-being, and that poor health is strongly associated with economic deprivation. Developing analytical tools for measuring health poverty, and its sources and distribution across groups and regions, has considerable potential to enable policymakers to identify vulnerable populations that might be amenable to policy interventions. The paper provides an illustration of how integrating medical data with open-access satellite data, including nighttime lights, enriches the analysis of health poverty determinants and spatial distribution compared to conventional socioeconomic indicators, particularly beneficial in developing regions. Nighttime light data have proved to be a useful supplement to more traditional economic indicators, particularly in developing countries where measures of SES are often not routinely available to researchers (Elvidge et al., 1997; Chen and Nordhaus, 2011).

2. Data

Our sample included data from 932,855 people in Peninsular Malaysia between the ages of 40 and 75 with diagnosed Type 2 diabetes (T2DM), registered in the National Diabetes Registry of Malaysia (NDR) between 1 January 2009 and 31 December 2018. The NDR contains date of diagnosis for all people in the database. We used 40 years as the age cutoff. This was to minimize the number of people in our dataset with type 1 diabetes, which typically presents and is diagnosed earlier in life than T2DM and has different properties (American Diabetes Association, 2010). We selected the year 2009 as the start date due to the transition of the NDR to a web-based data collection system, which enhanced data quality. The registry included the following variables at individual level: age, sex, hospital name and prevalence of comorbidities. The NDR was electronically linked to the National Death Registry up until 31 December 2019. Thus, date of death is available for all people in the NDR who had died by 31 December 2019.

We employed two different approaches to obtaining estimates of SES for analysis. As with most administrative health data, the NDR does not include socioeconomic indicators such as income or education. Instead, we used two alternatives. First, we used a districtlevel asset index developed using data from the 2010 census in Malaysia (Mariapun et al., 2016). Our second approach was to use luminosity (nighttime light data) as a measure of SES. This builds on an increasing body of literature, following Chen and Nordhaus (2011), which used luminosity as a useful proxy for economic welfare. A major advantage of this approach is that it is widely applicable as average nighttime luminosity can be obtained from imaging data that is openly accessible as shapefiles from the NOAA National Centers for Environmental Information (NCEI) website. The data are derived from specialized satellite sensors and provide large images containing nightlight intensities from around the world, taken from space. These images (in the form shapefiles) contain an annual cloudfree composite of average digital brightness value for the detected lights, filtered to remove ephemeral lights and background noise. We

used this satellite data on nighttime lights for the year 2013, the last available year in the NCEI website. The measure comes on a scale of 0–63 (higher values implying greater luminosity) and the data are available at high geographic resolution, with each pixel being equivalent to one km² (National Centers for Environmental Information-NCEI).

We used the software Q-Gis 3.20 to superimpose the map of Malaysia on the nighttime luminosity shapefile and extract the nighttime lights data in the country. As the NDR included the names of the hospital, we used Google maps to extract the hospitals' coordinates, locate them on the map and link them to the luminosity data. This allowed us to develop a much more granular measure of SES at the clinic level (based on average luminosity in the 1 Km² in the clinic where the person is registered) than using a district-level asset index. Our sample contained 88 districts and 635 hospital clinics, so on average each district-level asset value covered around 10,500 individuals, while our luminosity measure covered on average 1500 people attending each clinic.

Table 1 presents an overview of the sample used in the analysis, disaggregated by sex, and drawn from medical registries. The dataset comprises 57% females and 43% males. On average, males are registered in areas characterized by a slightly higher asset index and nighttime luminosity compared to females. Both genders exhibit similar age distributions, with approximately 40% falling within the 55 to 65 age bracket. Notably, the Central and Northern regions display the highest concentration of registered individuals. Furthermore, the prevalence of comorbidities is higher among males than females.

Table 1
Summary statistics.

Variable	Females		Males		Total	
	Mean	SD	Mean	SD	Mean	SD
DM Duration (years)	4.02	4.79	3.89	4.97	3.96	4.88
Asset Index	0.07	0.28	0.09	0.27	0.08	0.27
Luminosity	50.03	17.83	51.46	17.05	50.64	17.44
Variable	Mean	%	Mean	%	Mean	%
<i>Region:</i>						
Central	188,466	35.4	148,564	37.1	337,030	36.1
East Coast	88,774	16.7	59,510	14.8	148,284	15.9
Northern	168,611	31.7	126,567	31.6	295,178	31.6
Southern	86,116	16.2	66,247	16.5	152,363	16.3
<i>Age group:</i>						
40-45	64,024	12.0	45,008	11.2	109,032	11.7
45-50	65,402	12.3	46,675	11.6	112,077	12.0
50-55	92,980	17.5	65,038	16.2	158,018	16.9
55-60	105,966	19.9	78,340	19.5	184,306	19.8
60-65	92,808	17.4	75,825	18.9	168,633	18.1
65-70	65,953	12.4	54,859	13.7	120,812	13.0
70-75	44,834	8.4	35,143	8.8	79,977	8.6
<i>Comorbidities:</i>						
Diabetic foot	3,703	0.7	4,102	1.0	7,805	0.8
Nephropathy	26,491	5.0	25,054	6.2	51,545	5.5
Retinopathy	22,477	4.2	16,498	4.1	38,975	4.2
IHD	18,316	3.4	23,218	5.8	41,534	4.5
Stroke	5,442	1.0	6,417	1.6	11,859	1.3
Amputation	2,103	0.4	2,591	0.6	4,694	0.5
Sample size (N)	531,967		400,888		932,855	

Note: Asset index and luminosity data were based on hospital of registration.

3. Methods

It is widely recognized that any attempt to measure poverty requires the following steps: firstly, to define the relevant indicator of welfare; secondly, to establish a minimum acceptable standard for that indicator (often referred to as a poverty line); finally, to employ a summary statistic to quantify information on the distribution of this welfare indicator relative to the poverty line (e.g., Haughton and Khandker (2009)).

The present study employs 5-year survival rate as a measure of wellbeing. This indicator has conventionally been used in the context of cancer outcomes (Howe et al., 2001; Verdecchia et al., 2007; Sankaranarayanan et al., 2010), but its applicability has been extended to stroke patients (Smajlović et al., 2006) and elderly individuals diagnosed with diabetes (The Bypass Angioplasty Revascularization Investigation (BARI), 1997). To estimate the 5-year survival probability of each participant, a stratified Cox proportional hazards model was employed. We measured health poverty through an adaptation of the Foster-Greer-Thorbecke family of poverty indices (Clarke and Erreygers, 2020). We apply the approach of Clarke and Erreygers (2020) by conceptualising health poverty as a specific indicator of early mortality, i.e. having a 5-year survival probability that is significantly lower than that which would be expected for someone of the same age and sex.

3.1. Quantifying five-year survival

Equation (1) shows the Cox proportional hazards model employed in the present study, stratified by age group and gender, and adjusted for relevant covariates that could potentially affect survival time:

$$h(t|X) = h_0(t) \times \exp(\beta_1(1) \text{ Region} + \beta_2(2) \text{ Luminosity} + \beta_3(3) \text{ AssetIndex} + \beta_4 \text{ Duration of Diabetes} + \beta_5 \text{ Comorbidities}) \quad (1)$$

The hazard function $h(t)$ represents the hazard at time t for a subject with covariates X : region, luminosity, asset index, comorbidities, and time since diagnosis of diabetes. The impact of these covariates is assumed to be proportional over time, and they act multiplicatively on the baseline hazard so that the hazard of the event in any group is a (constant) multiple of the hazard in any other. The term h_0 is the baseline hazard at time t , and it represents the value of the hazard for a subject with all their covariates equal to zero. The quantities $\exp(\beta_i)$ represent the hazard ratios (HR). A value of β_i greater than zero, or equivalently, a hazard ratio greater than one, indicates that as the value of the i th covariate increases, the event hazard increases, and thus the length of survival decreases (Clark et al., 2003).

The survival probability (survivor function), $S(t)$, is the probability that an individual survives from the time origin (e.g. age of registry at the hospital) to a specified future time t , in our case $t = 5$. Survival times do not follow a particular statistical distribution because the baseline hazard function is estimated non-parametrically (Clark et al., 2003). However, in cases when a variable violates the proportional hazard assumption, stratification allows to estimate the model separately in each stratum. This way, the baseline hazard function, $h_0(t)$, can be different across strata. After performing a proportional hazards test, we decided to stratify the database by sex (males and females), and 5-year age groups (7 in total: 40 to 45, 45 to 50, 50 to 55, 55 to 60, 60 to 65, 65 to 70, and 70 to 75).

Our estimation procedure has two key advantages: first, individual five-year survival is conditioned on a range of explanatory variables, and second, the sex and age-group stratification. The first helps us identify which factors affect an individual's risk profile over time and mitigate potential confounding variables on survival outcomes. The second offers a robust approach to address potential variations in age and sex composition across regions. We used the R package 'survival' for the analysis.

3.2. Defining a health poverty line

There is an extensive literature and well established approaches to setting income poverty lines (Atkinson, 1987; Allen, 2017; Ravallion, 2020). In contrast, when it comes to assessing health shortfalls, the literature on setting thresholds for health poverty measures is in its infancy. Views may legitimately differ as to how far survival probability should fall below that of the age and sex adjusted general population in order to be deemed to constitute health poverty. (This is analogous to the situation in measuring income poverty, where there can be a range of views as to how high an income poverty line should be.) To capture these different judgements as to what should be considered health poverty, we used two thresholds. Use of the higher threshold, demanding a survival probability closer to the general population, would register higher levels of health poverty, as requiring survival probability to exceed this threshold is more demanding. Conversely, the lower threshold allows for larger shortfalls from the general population without penalty. Using both thresholds together permits a more nuanced understanding of the nature and extent of health poverty. These two thresholds are the following: i.) a 5%, and ii) a 10% absolute reduction in five-year survival compared with age-sex matched five-year survival of the general Malaysian population. At the higher threshold, people were deemed ‘health poor’ if their 5-year survival probability was more than 5% below that of the age and sex adjusted general Malaysia population. At the lower threshold, people were deemed health poor if their 5-year survival probability was more than 10% below that of the age and sex adjusted general Malaysia population. Hua et al. (2020) estimated that, to provide an intuitive interpretation of this threshold, smoking reduced the five-year survival rate of people with diabetes by around 1%, on average. We also report 5% and 10% relative risk reductions in supplementary analyses.

3.3. Quantifying health poverty

Our health outcome variable, five-year survival probability, has ratio-scale properties. This means that, for those individuals who do not reach the threshold and are ‘health poor’, we can give a meaning to the distance between their health and a given threshold level (the ‘health gap’) (Clarke and Erreygers, 2020).

Applying the Foster-Greer-Thorbecke (FGT) class of poverty indicators (Foster et al., 1984) enables us to assess the prevalence, intensity and severity of health poverty, as shown in Eq. (2):

$$P_{\alpha} = \frac{1}{n} \sum_{i=1}^q (g_i)^{\alpha} \quad (2)$$

where:

$$g_i = \begin{cases} \frac{z - S(t)_i}{z}, & \text{if } S(t)_i < z \\ 0, & \text{if } S(t)_i \geq z \end{cases}$$

In Eq. (2), n refers to the total sample; q is the number of people with a survival probability below the threshold, and g_i is the size of the gap, i.e. for an individual i who lies below the threshold, the difference between individual i 's survival probability, $S(t)_i$, and the survival probability threshold, z . The health gap is equal to zero for individuals that lie above the threshold. α , also known as the *poverty aversion parameter*, assigns increasing importance to those whose deprivation is far below the threshold, with different values having diverse interpretations (Foster et al., 1984, 2010, 2013; Asada, 2007):

- P_0 : represents the headcount poverty ratio, or the proportion of people below the poverty threshold
- P_1 : represents the intensity of health poverty. It is also known as the health-gap index. As we are quantifying health poverty using a five-

year survival probability, the gap measure has an intuitive interpretation, in that the numerator $z - S(t)_i$ is the degree to which survival falls below the threshold.

- P_2 : represents the severity of health poverty. Also known as the squared gap measure, it weights the gaps by the gap size itself.

We calculate health poverty by sex, age group, and district.

While there are well developed methods for decomposing poverty measures using regression methods (Wagstaff et al., 2001), these would require some re-formulation to be applied to measures of health poverty when applied to survival data. To take a step in this direction, we conducted simulations to estimate the associations between health poverty and comorbidities of diabetes (which are often used as a marker of the severity of the disease) as well as SES. To perform these, we considered two (separate) counterfactual scenarios: first, that individuals had no comorbidities; and second, that all individuals lived in a relatively developed area with high average SES (proxied by setting luminosity everywhere as equal to that of the highest luminosity areas in our dataset). We re-estimated our poverty measures under each of these counterfactual scenarios to assess the extent to which these factors contribute to P_0 .

Ethical approval

Ethical approval for this study was obtained from the Medical Research and Ethics Committee (MREC), Ministry of Health Malaysia (NMRR-19-356652314).

4. Results

4.1. Health poverty

We estimated the 5-year survival probability of each participant based on the results of the Cox model, and compared it to the official life tables of the Malaysian population in 2015 (Department of Statistics of Malaysia, 2017). Across all age groups, 5-year survival probability for the sample is lower than the country figures, and these shortfalls are substantially larger among men than women (see Appendix- Table 3). For instance, while the survival probability of the oldest age group in our sample (70–75 years) is 0.05 below the official life tables in the case of females, it is 0.08 below the official life tables in the case of males.

Fig. 1 shows the multivariable adjusted hazard ratios of risk factors

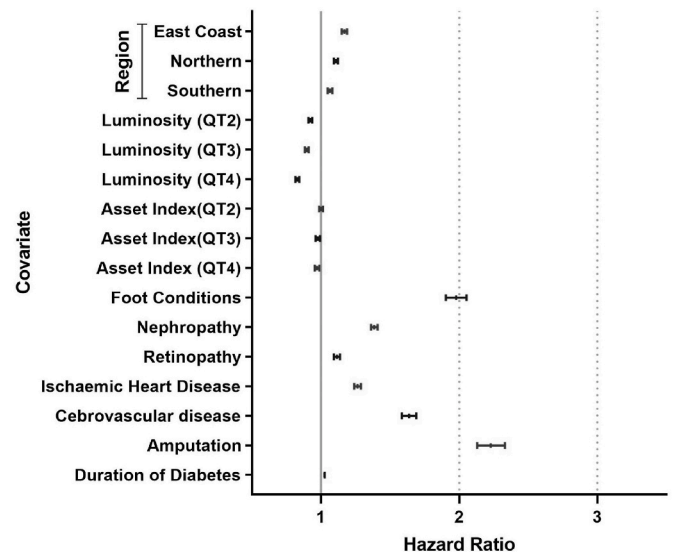


Fig. 1. Relevance of covariates to 5-year mortality at ages 40–75 years (in hazard ratios).

associated with 5-year mortality for males and females. The model included the following covariates: region, age group, asset index (in quartiles), average nighttime luminosity (in quartiles), duration of diabetes at registration, and prevalence of: diabetic foot, nephropathy, retinopathy, ischemic heart disease (IHD), stroke, and amputation. Results show that living in the east coast, northern or southern regions increases the risk of mortality among males and females of the sample, compared to males and females living in the central region. Older age groups have an increased risk of mortality over the reference 40–45 years age group. Hazard ratios for females are higher than for males, suggesting that age has a higher relative impact on mortality for females. Both the average nighttime luminosity and asset index are protective factors for mortality, in males and females alike. Comorbidities increase the hazard and each additional year of diabetes duration is associated with a higher mortality hazard among both males and females, though this hazard is slightly higher for the latter group. The values and confidence intervals of the hazards ratios can be found in the appendix (Table 4).

Views may legitimately differ as to how far survival probability should fall below that of the age- and sex-adjusted general population in order to be deemed to constitute health poverty. This is analogous to the situation in measuring income poverty, where there can be a range of views as to how high an income poverty line should be. To capture these different judgements as to what should be considered health poverty, we used two thresholds. Use of the higher threshold, demanding a survival probability closer to the general population, would register higher levels of health poverty, as requiring survival probability to exceed this threshold is more demanding. Conversely, the lower threshold allows for larger shortfalls from the general population without penalty. Using both thresholds together permits a more nuanced understanding of the nature and extent of health poverty.

As previously explained, thresholds were set in reference to the age and sex adjusted mortality rates of the general Malaysia population presented in the life tables. At the higher threshold, people were deemed ‘health poor’ if their 5-year survival probability was more than 5% below that of the age and sex adjusted general Malaysia population. At the lower threshold, people were deemed health poor if their 5-year survival probability was more than 10% below that of the age and sex adjusted general Malaysia population. Notably, the higher threshold (5%) requires a survival probability closer to that of the general Malaysian population for it to be considered out of health poverty, rendering it a more stringent criterion.

Using the higher (5 pp) threshold, 43% of the sample (23% of females and 71% of males) live in health poverty (P_0). Using the lower (10 pp) threshold 9% (5% (females) and 14% (males)) live in health poverty (Table 2). Results for the two thresholds are somewhat heterogeneous by age group. Using the higher threshold, the head-count ratio (P_0) is

Table 2
Health poverty in Malaysia.

Age group	High threshold (–5%)			Low threshold (–10%)		
	P_0	P_1	P_2	P_0	P_1	P_2
40–45 years	0.0689	0.0011	0.0001	0.0046	0.0003	0.0000
45–50 years	0.4370	0.0103	0.0006	0.0288	0.0014	0.0002
50–55 years	0.4589	0.0132	0.0010	0.0503	0.0025	0.0004
55–60 years	0.4981	0.0173	0.0017	0.0807	0.0043	0.0007
60–65 years	0.5335	0.0241	0.0029	0.1275	0.0079	0.0015
65–70 years	0.4984	0.0309	0.0049	0.1651	0.0129	0.0027
70–75 years	0.4352	0.0392	0.0082	0.1936	0.0202	0.0051
By sex:						
- Males	0.7079	0.0292	0.0034	0.1358	0.0087	0.0017
- Females	0.2293	0.0108	0.0017	0.0546	0.0045	0.0010
Overall:	0.4350	0.0187	0.0024	0.0895	0.0063	0.0013

Note: At the higher (lower) threshold, people were deemed health poor if their 5-year survival probability was more than 5(10)% below that of the age and sex adjusted general Malaysia population.

relatively constant across age-groups (except 40–45 years), whereas using the low threshold there is a clear age gradient. This age-gradient in poverty is also observed when using the health-gap index (P_1) and squared-gap (P_2). Supplementary analysis show the results by sex. In females, the higher prevalence of health poverty occurs at older ages, while for males health poverty peaks at age 45 to 50, and then slowly declines (using the higher threshold). In all age groups, and using all thresholds, health poverty is higher for males than for females.

Fig. 2 shows the relationship between health poverty rates, signaled in the y-axis, and socioeconomic indicators (Asset Index and Luminosity), in the x-axis, by district. The size of the bubbles represents the population size of each district, as reported by the Department of Statistics of Malaysia. There is a strong negative relationship between health poverty and luminosity, with a correlation of -0.76 ; and between health poverty and the asset index, with a correlation of -0.82 .

The size of the bubbles represent the population in the district, whereas the color represents the level of urbanization.

4.2. Simulation results

Fig. 3-A maps the head-count ratio (P_0) onto the 88 districts in Peninsular Malaysia to provide a visual representation of the geographical distribution of our health poverty measures. Districts in the west coast of Malaysia tend to have lower health poverty rates, whereas the districts of Lipis, Gua Musang, Tanah Merah and Jeli have the highest rates of health poverty. Petaling, Hulu Langat, and Gombak have the lowest rates of health poverty, below 20%.

We ran simulations under two scenarios. First, we eliminated the presence of comorbidities. Under this scenario, health poverty decreased 5.4% for females and 2.9% for males, using the higher threshold; and 3.4% for females and 7.4% for males, using the lower threshold (Tables 5 and 6 in the Appendix). Although districts experience a fall in their health poverty rates, these falls are rather modest for the districts with greatest health poverty. For instance, in Lipis, health poverty falls from 83% to 82%, and in Jeli from 78% to 77% (see Fig. 3-B). In general, the 10 districts with the highest health poverty only lower their rates by 1 or 2%.

Under the second scenario, we set luminosity in all districts as equal to that of the highest luminosity areas in our dataset. Health poverty decreased 4.6% for females and 5.8% for males, using the higher threshold; and 0.8% for females and 4.1% for males, using the lower threshold (Tables 7 and 8 in the Appendix). All districts show decreases in their health poverty rates, but these falls are more extreme among districts with high health poverty rates, in some cases presenting falls of more than 20%. For instance, in Lipis, health poverty would drop from 83% to 57%, and in Jeli from 78% to 54% (see Fig. 3-C). This suggests that luminosity, our socioeconomic proxy, is strongly associated with health poverty.

Health poverty decreases under both scenarios, compared to the baseline scenario. Furthermore, the decrease in the P_1 index suggests that, for those who remain health-poor under these scenarios, their health index lies closer to the healthy threshold. It is noteworthy that P_1 decreases more sharply under Scenario 2 (highest luminosity) than under Scenario 1 (no comorbidities), in particular for females, wherein the P_1 index value halves (from 0.011 to 0.005). The latter suggests a bigger impact of luminosity for the average outcomes of the health-poor.

Similarly, the P_2 index decreases under both scenarios, compared to the baseline scenario. The decrease in P_2 suggests a less unequal distribution of health poverty among those who remained health-poor, so under both scenarios there are less extreme values in the distribution for the outcomes of the health-poor, compared to the baseline scenario.

P_2 decreases more sharply under Scenario 2 (highest luminosity) than under Scenario 1 (no comorbidities). In the former, the P_2 index value lowers by over 70% compared to the baseline scenario.

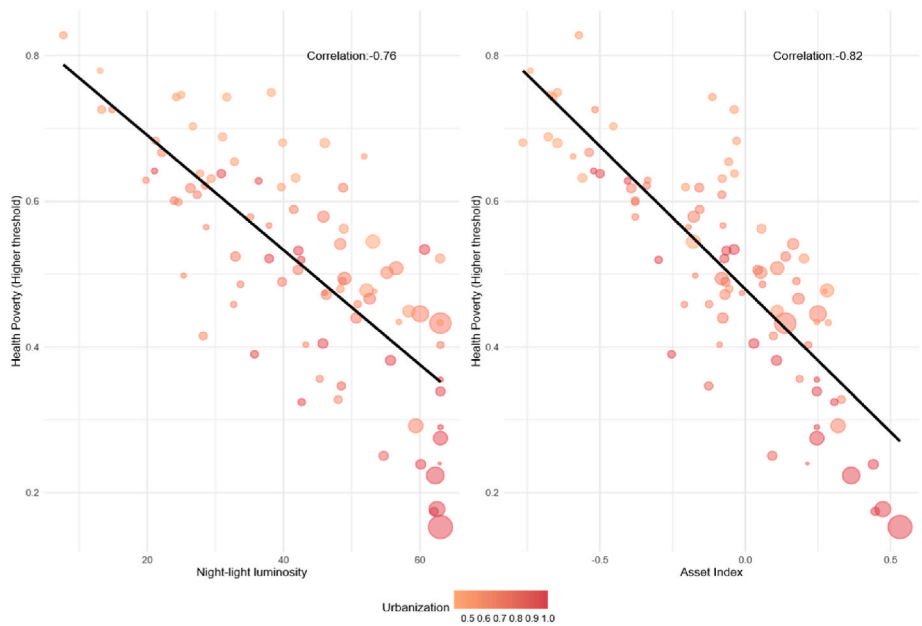


Fig. 2. Health poverty ratio and luminosity (left) and asset index (right), by district.

A Health Poverty in Malaysia

B Health Poverty in Malaysia (No Comorbidities)

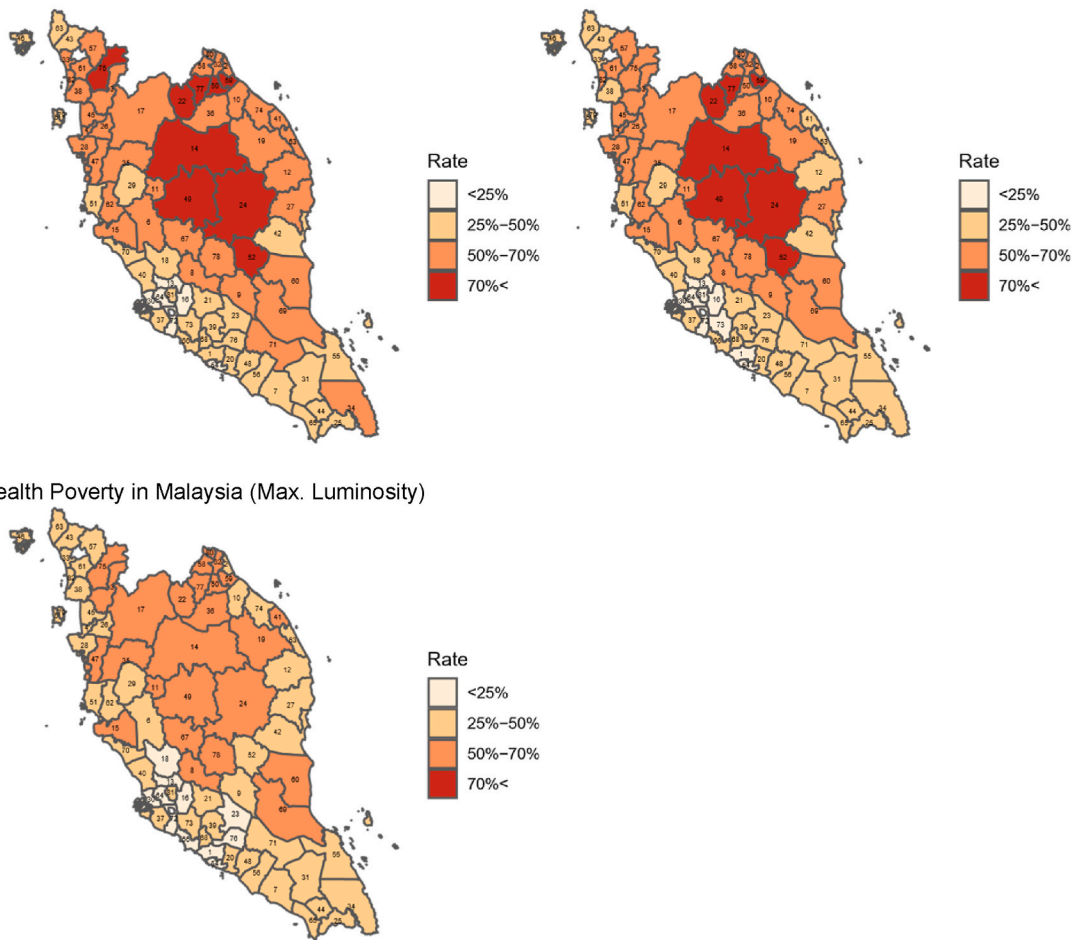


Fig. 3. Health poverty ratio by district (district key in Appendix).

5. Discussion

We find that, across all age groups, the 5-year survival probability values are lower for the NDR dataset compared to the country figures, with around 43% of the sample deemed to be in health poverty using the higher (5%) threshold and around 9% at the lower (10%) threshold. For most FGT measures, poverty tended to increase with age, and males consistently had higher health poverty rates than females. The districts with the highest health poverty levels are also the most economically deprived or with lower night time luminosity.

Districts in the west coast of Malaysia (such as Petaling, Hulu Langat and Gombak) tend to have lower health poverty rates (between 15% and 18%) and highest luminosity, whereas districts in the north-centre of the country (such as Lipis, Gua Musang, Tanah Merah and Jeli) have the highest rates of health poverty (between 75% and 83%).

To further understand how levels of poverty are associated with factors that may be amenable to policy changes we undertook two simulations. Firstly, we re-estimated the five-year survival probabilities assuming that registry participants were free of diabetes-related complications. Health poverty rates, as measured by the headcount ratio, declined 4.3% at the 5% threshold and 5.1% at the 10% threshold. Secondly, we looked at the associations with levels of luminosity and simulated the survival probabilities in the scenario that all people lived in an area of highest night-light intensity. Under this scenario, poverty is 5.1% overall at the higher threshold and 2.2% at the lower threshold, although the luminosity simulation had a greater impact on the spatial distribution of health poverty (see Fig. 3). While these counterfactual simulation results should not be interpreted as causal effects, they do provide an illustration of how health poverty analysis and mapping may inform policy evaluations of strategies to improve diabetes care in Malaysia. Given that the Malaysian NDR also collects both information on common metabolic factors such as HbA1c, a measure of glycaemia, as well as medication use (Ministry of Health Malaysia, 2021), there is considerable scope for further poverty analyses and policy evaluation.

While socioeconomic measures such as income have been shown to stratify survival of older people with diabetes in high-income countries such as Japan (e.g. see Jiang et al. (2020)), income information is not routinely collected in administrative health data sets such as the Malaysian NDR. Instead, we explore how nighttime luminosity, which although it is increasingly used as a measure of development (Chen and Nordhaus, 2011) and income inequality (Mirza et al., 2021), has not been utilised for risk stratification, or to measure health inequalities. Our results suggest that levels of luminosity are an independent predictor of five-year survival among people with diabetes over both a district-level asset index and a range of common clinical risk-factors (see Fig. 1). At a district level, there is a strong correlation between levels of luminosity and health poverty. Given the difficulties of measuring income in many low and middle income countries, there is great potential to retrospectively attach luminosity data (or recently developed micro-estimates of wealth that have been developed using luminosity and a range of other indicators such as mobile phone use (Chi et al., 2022)) to existing health outcomes, and use this data to much better understand socioeconomic-related health inequalities.

Our findings on the spatial distribution of health poverty are aligned with the literature on social determinants of health identified as having an impact on diabetes outcomes. In their review, though mostly using U. S.-based studies, Hill-Briggs et al. (2020) identify evidence of associations of SES, neighborhood and physical environment, food environment, health care and social context with diabetes-related outcomes. There is potential to gain a great understanding of the role of physical environment in health by employing *changes* data on luminosity, as well other factors such as pollution, which a recent literature review concludes are linked with insulin resistance and diabetes (Meo et al., 2015).

In this study we used five-year survival as our welfare indicator, as it is a metric that clinicians often use to convey outcomes to patients (Bell et al., 2018; Hua et al., 2020), and has even featured in media, including

an article by the Times of India (Times of India, 2021). We employed two thresholds and our results suggest that the levels of health poverty are quite sensitive to which threshold is chosen. While our main results report thresholds based on an absolute reduction in survival compared with the general population, it is also possible to define a relative health poverty line. Deciding between different thresholds has parallels with the measurement of income poverty both at a national (eg. see Foster (1998)) and international level (Dhonde and Minoiu, 2013). In this regard, some methodological research that potentially builds on efforts to measure income poverty (Callan and Nolan, 1991) would be welcome.

Another measurement issue is that our poverty estimates are based on an equation to predict 5-year survival probability rather than actual duration of survival. This will mean that multiple individuals with the same characteristics will have the same survival probability, whereas their actual duration of survival may be very different. This has parallels in poverty and income inequality measures such as the Gini index, where it is well-known that using grouped data reduces the magnitude of these statistics due to not being able to quantify within-group inequalities. A variety of corrections have been proposed (e.g. see Minoiu and Reddy (2008)) and again it would be useful to explore these issues in further work.

Our study has several limitations. Firstly, we were unable to control for factors such as education and income, which have an important role in stratifying health outcomes of the sample. We aimed to partially overcome the lack of socioeconomic variables by using measures of luminosity, but ideally having both individual and area level SES measures would enrich future analyses. Similarly, we did not have information on metabolic risk factors such as blood pressure, or the use of medications as these were not collected at the registration visit. The NDR also collects additional information on a random sub-set of registry participants (Ministry of Health Malaysia, 2020). This includes complications of diabetes, risk factors such as hypertension, dyslipidaemia and glycaemic control (HbA1c), and their use of drug treatments for diabetes and concomitant conditions. Thus, there is potential to expand the analysis in future research to identify treatment gaps in future. Beyond clinical measures, it would be useful to have information on quality-of-life as this would assist in both defining health poverty and in developing holistic outcomes such as QALYs.

Our study has also illustrated how standard approaches to measuring socioeconomic inequalities, such as estimating the gradient in risk using a Cox regression model, can be supplemented with poverty measures. For example, the poverty maps in Fig. 3, which report proportions falling below key poverty thresholds, clearly illustrate the geographic variation in mortality across Malaysia. The health poverty approach we adopt is very flexible and has considerable potential for different applications, for example, by using poverty thresholds based on clinical guidelines. The availability of large databases including biomarkers, and potential linkage with national data at regional (and even neighborhood) level, offers scope for methodological improvements in the building of an index of health poverty. Along with early mortality, clinically important variables with convenient properties for measuring health poverty include: risk of cardiovascular disease (CVD) and biomarkers (i.e. cholesterol and triglycerides, C-reactive protein (CRP), fibrinogen, haemoglobin and ferritin levels). Drawing on clinical guidance, we can determine threshold levels of the minimum desirable standards of such health variables, and so calculate a health gap as the distance between an individual's health achievement and the relevant clinical threshold level (adjusted by group-characteristics). Using clinical thresholds would enable the production of simulations of how much health can be improved (or health poverty alleviated) by offering low-cost treatments to patients with risk levels that exceed certain thresholds. The availability of existing large databases including biomarkers (including the WHO Stepwise Approach to Surveillance (STEPS) (Bonita et al., 2003)), some of which can be linked to external data such as information on mortality and morbidity, offers a scope for widening the

application of health poverty and inequality measures to LMICs. A key avenue for future research is in using health poverty measures to identify people who are at high risk, or in poor health, and then assess the scope for interventions that can improve their health outcomes. For instance, a recent study looking at the level of the cholesterol lowering drug statins in 41 LMICs found their use was well below WHO guidelines and argued for an “urgent need to scale up statin use in LMICs to achieve WHO targets” (Marcus et al., 2022). The availability of global luminosity data also opens up the possibility of estimating global trends in health inequality and poverty alongside attempts to monitor income poverty (Bank, 2020). Such measures should enrich our understanding of the multi-dimensional nature of poverty and help provide evidence to better deal with current and future challenges.

6. Conclusion

This paper applies a recently proposed approach to measuring health poverty to people in Malaysia with T2DM. We find that, across all age groups, the 5-year survival probability values for people with diabetes

are lower than those of the age and sex adjusted national population. We find that nighttime lights and a district-level asset based index are strongly associated with health poverty. The spatial distribution of health poverty matches that of nighttime luminosity maps: districts in the west coast of Malaysia tend to have lower health poverty rates and highest nighttime luminosity values, whereas districts in the northcentre of the country have the highest rates of health poverty. Incorporating easily and widely available luminosity data into medical datasets offers the potential for improved risk stratification and measurement of health inequalities across a wide range of settings, particularly in contexts where socioeconomic data are limited. This enables identification of groups and regions that are disproportionately affected, allowing for targeted interventions to reduce health disparities and promote health equity.

Data availability

The data that has been used is confidential.

Appendix

Survival probabilities

Table 3

Survival probabilities in diabetes sample versus general population, by age group

Agegroup	S(t = 5)		Lifetables	
	Females	Males	Females	Males
40–45 years	0.97	0.94	0.99	0.98
45–50 years	0.95	0.90	0.98	0.97
50–55 years	0.93	0.88	0.97	0.95
55–60 years	0.91	0.85	0.96	0.93
60–65 years	0.88	0.82	0.93	0.89
65–70 years	0.83	0.77	0.89	0.84
70–75 years	0.76	0.69	0.81	0.77

Hazard ratios for five-year mortality (males and females)

Table 4

Hazard Ratios and 95% Confidence Intervals for Covariates

Covariate	Hazard ratio	Lower CI	Upper CI
East Coast	1.17	1.15	1.19
Northern	1.11	1.09	1.12
Southern	1.06	1.05	1.08
Luminosity (Q2)	0.92	0.91	0.94
Luminosity (Q3)	0.90	0.88	0.91
Luminosity (Q4)	0.83	0.81	0.84
Asset index (Q2)	1.00	0.99	1.01
Asset index (Q3)	0.98	0.96	0.99
Asset index (Q4)	0.97	0.95	0.99
Diabetic feet	1.98	1.90	2.05
Nephropathy	1.39	1.36	1.41
Retinopathy	1.12	1.09	1.14
Ischemic heart disease	1.27	1.24	1.29
Cerebrovascular disease	1.64	1.59	1.69
Amputation	2.23	2.13	2.33
Duration of Diabetes	1.03	1.02	1.03

Simulation results

Table 5
Health poverty and inequality in Malaysia under Scenario 1: No comorbidities (overall)

	High threshold (-5%)			Low threshold (-10%) Age group		
	P_0	P_1	P_2	P_0	P_1	P_2
40–45 years	0.0430	0.0002	0.0000	0.0001	0.0000	0.0000
45–50 years	0.4102	0.0073	0.0002	0.0058	0.0001	0.0000
50–55 years	0.4236	0.0086	0.0003	0.0147	0.0002	0.0000
55–60 years	0.4583	0.0105	0.0004	0.0291	0.0005	0.0000
60–65 years	0.4871	0.0139	0.0007	0.0568	0.0014	0.0001
65–70 years	0.4353	0.0165	0.0012	0.0812	0.0030	0.0003
70–75 years	0.3565	0.0193	0.0021	0.1017	0.0055	0.0007
Overall	0.3916	0.0107	0.0006	0.0384	0.0013	0.0001

Note: At the higher (lower) threshold, people were deemed health poor if their 5-year survival probability was more than 5(10)% below that of the age and sex adjusted general Malaysia population.

Table 6
Health poverty and inequality in Malaysia under Scenario 1: No comorbidities (by sex)

Age group	High Threshold (-5%)					
	P_0		P_1		P_2	
	Females	Males	Females	Males	Females	Males
40–45 years	0.0012	0.1025	0.0000	0.0006	0.0000	0.0000
45–50 years	0.0439	0.9236	0.0004	0.0170	0.0000	0.0005
50–55 years	0.1198	0.8579	0.0015	0.0187	0.0000	0.0006
55–60 years	0.1973	0.8113	0.0033	0.0203	0.0001	0.0008
60–65 years	0.2813	0.7389	0.0067	0.0227	0.0004	0.0012
65–70 years	0.3260	0.5666	0.0121	0.0217	0.0010	0.0014
70–75 years	0.2382	0.5075	0.0140	0.0261	0.0018	0.0024
Overall	0.1753	0.6785	0.0048	0.0186	0.0004	0.0009
Low threshold (-10%)						
40–45 years	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000
45–50 years	0.0003	0.0135	0.0000	0.0001	0.0000	0.0000
50–55 years	0.0020	0.0328	0.0000	0.0004	0.0000	0.0000
55–60 years	0.0081	0.0576	0.0002	0.0009	0.0000	0.0000
60–65 years	0.0259	0.0946	0.0009	0.0021	0.0001	0.0001
65–70 years	0.0630	0.1031	0.0028	0.0031	0.0003	0.0002
70–75 years	0.0758	0.1348	0.0052	0.0060	0.0008	0.0006
Overall	0.0207	0.062	0.001	0.0016	0.0001	0.0001

Note: At the higher (lower) threshold, people were deemed health poor if their 5-year survival probability was more than 5(10)% below that of the age and sex adjusted general Malaysia population.

Table 7
Health poverty and inequality in Malaysia under Scenario 2: Maximum Luminosity (overall)

	High threshold (-5%)			Low threshold (-10%) Age group		
	P_0	P_1	P_2	P_0	P_1	P_2
40–45 years	0.0341	0.0008	0.0001	0.0038	0.0002	0.0000
45–50 years	0.4207	0.0081	0.0005	0.0207	0.0011	0.0002
50–55 years	0.4265	0.0104	0.0008	0.0360	0.0020	0.0003
55–60 years	0.4513	0.0136	0.0013	0.0583	0.0034	0.0006
60–65 years	0.4727	0.0189	0.0023	0.0945	0.0064	0.0012
65–70 years	0.4070	0.0244	0.0040	0.1288	0.0106	0.0023
70–75 years	0.3482	0.0314	0.0067	0.1520	0.0166	0.0043
Overall	0.3839	0.0148	0.002	0.0673	0.0051	0.0011

Note: At the higher (lower) threshold, people were deemed health poor if their 5-year survival probability was more than 5(10)% below that of the age and sex adjusted general Malaysia population.

Table 8
Health poverty and inequality in Malaysia under Scenario 2: Maximum Luminosity (by sex)

Age group	High Threshold (-5%)					
	P_0		P_1		P_2	
	Females	Males	Females	Males	Females	Males
40–45 years	0.0104	0.0676	0.0004	0.0015	0.0000	0.0001
45–50 years	0.0669	0.9165	0.0017	0.0172	0.0002	0.0009

(continued on next page)

Table 8 (continued)

Age group	High Threshold (-5%)					
	P_0		P_1		P_2	
	Females	Males	Females	Males	Females	Males
50–55 years	0.1337	0.8450	0.0038	0.0199	0.0004	0.0013
55–60 years	0.1999	0.7914	0.0068	0.0227	0.0008	0.0020
60–65 years	0.2748	0.7150	0.0122	0.0271	0.0017	0.0031
65–70 years	0.3221	0.5089	0.0206	0.0289	0.0035	0.0045
70–75 years	0.2687	0.4497	0.0262	0.0380	0.0060	0.0077
Overall	0.1832	0.6503	0.0091	0.0223	0.0015	0.0026
	Low threshold (-10%)					
	P_0		P_1		P_2	
	Females	Males	Females	Males	Females	Males
40–45 years	0.0021	0.0064	0.0001	0.0004	0.0000	0.0000
45–50 years	0.0070	0.0399	0.0005	0.0020	0.0001	0.0003
50–55 years	0.0166	0.0637	0.0011	0.0033	0.0002	0.0005
55–60 years	0.0327	0.0928	0.0022	0.0051	0.0005	0.0008
60–65 years	0.0640	0.1318	0.0046	0.0085	0.0010	0.0016
65–70 years	0.1125	0.1483	0.0095	0.0119	0.0021	0.0025
70–75 years	0.1282	0.1825	0.0148	0.0189	0.0040	0.0046
Overall	0.0465	0.095	0.0039	0.0067	0.0009	0.0013

Note: At the higher (lower) threshold, people were deemed health poor if their 5-year survival probability was more than 5(10)% below that of the age and sex adjusted general Malaysia population.

Fig. 3: District key

Alor Gajah (1) Bachok (2) Baling (3) Bandar Baharu (4) Barat Daya (5) Batang Padang (6) Batu Pahat (7) Bentong (8) Bera (9) Besut (10) Cameron Highlands (11) Cheras (12) Dungun (13) Gombak (14) Gua Musang (15) Hilir Perak (16) Hulu Langat (17) Hulu Perak (18) Hulu Selangor (19) Hulu Terengganu (20) Jasin (21) Jelebu (22) Jeli (23) Jempol (24) Jerantut (25) Johor Bahru (26) Kampar (27) Kemaman (28) Kepong (29) Kerian (30) Kinta (31) Klang (32) Kluang (33) Kota Bharu (34) Kota Setar (35) Kota Tinggi (36) Kuala Kangsar (37) Kuala Krai (38) Kuala Langat (39) Kuala Muda (40) Kuala Pilah

(41) Kuala Selangor (42) Kuala Terengganu (43) Kuantan (44) Kubang Pasu (45) Kulaijaya (46) Kulim (47) Langkawi (48) Larut Matang (49) Ledang (50) Lembah Pantai (51) Lipis. (52) Machang (53) Manjung (54) Maran (55) Marang (56) Melaka Tengah (57) Mersing (58) Muar (59) Padang Terap (60) Pasir Mas (61) Pasir Puteh (62) Pekan (63) Pendang (64) Perak Tengah (65) Perlis (66) Petaling (67) Pontian (68) Port Dickson (69) Raub (70) Rembau (71) Rompin (72) Sabak Bernam (73) Seberang Perai Selatan (74) Seberang Perai Tengah (75) Seberang Perai Utara (76) Segamat (77) Sepang (78) Seremban (79) Setiu (80) Sik (81) Tampin (82) Tanah Merah (83) Temerloh (84) Timur Laut (85) Titiwangsa (86).

Tumpat (87) Yan (88).

References

- Agarwal, S., Wade, A.N., Mbanya, J.C., Yajnik, C., Thomas, N., Egede, L.E., Campbell, J. A., Walker, R.J., Maple-Brown, L., Graham, S., 2023. The role of structural racism and geographical inequity in diabetes outcomes. *Lancet* 402, 235–249. <https://www.sciencedirect.com/science/article/pii/S0140673623009091>.
- Allen, R.C., 2017. Absolute poverty: when necessity displaces desire. *Am. Econ. Rev.* 107, 3690–3721. <https://doi.org/10.1257/aer.20161080>. <https://www.aeaweb.org/articles?id=10.1257/aer.20161080>.
- American Diabetes Association, 2010. Diagnosis and classification of diabetes mellitus. *Diabetes Care* 33 (Suppl. 1), S62. <https://doi.org/10.2337/dc10-S062>, 9.
- Asada, Y., 2007. *Health Inequality : Morality and Measurement*. University of Toronto Press, Toronto, UNKNOWN.
- Atkinson, A.B., 1987. On the measurement of poverty. *Econometrica* 55, 749–764. URL: <http://www.jstor.org/stable/1911028>. doi:10.2307/1911028.
- Bank, W., 2020. Poverty and shared prosperity 2020: reversals of fortune. <https://www.worldbank.org/en/publication/poverty-and-shared-prosperity> doi:10.1596/978-1-4648-1602.
- Bell, N.R., Dickinson, J.A., Grad, R., Singh, H., Kasperavicius, D., Thombs, B.D., 2018. Understanding and communicating risk: measures of outcome and the magnitude of benefits and harms. *Canadian family physician. Medecin de famille canadien* 64, 181–185.
- Bonita, R., Winkelman, R., Douglas, K.A., de Courten, M., 2003. *The WHO Stepwise Approach to Surveillance (Steps) of Non-communicable Disease Risk Factors BT Global Behavioral Risk Factor Surveillance*. Springer US, pp. 9–22.
- Callan, T., Nolan, B., 1991. *CONCEPTS OF POVERTY AND*.
- Chen, X., Nordhaus, W.D., 2011. Using luminosity data as a proxy for economic statistics. In: *Proceedings of the National Academy of Sciences of the United States of America*, vol. 108, pp. 8589–8594. <https://doi.org/10.1073/pnas.1017031108>.
- Chi, G., Fang, H., Chatterjee, S., Blumenstock, J.E., 2022. Microestimates of wealth for all low- and middle-income countries. In: *Proceedings of the National Academy of Sciences*, vol. 119, e2113658119. <https://doi.org/10.1073/pnas.2113658119> doi: 10.1073/pnas.2113658119.
- Clark, T.G., Bradburn, M.J., Love, S.B., Altman, D.G., 2003. Survival Analysis Part I: basic concepts and first analyses. *Br. J. Cancer* 89, 232–238. <https://doi.org/10.1038/sj.bjc.6601118> doi:10.1038/sj.bjc.6601118.
- Clarke, P., Erreygers, G., 2020. Defining and measuring health poverty. *Soc. Sci. Med.* 244 <https://doi.org/10.1016/j.socscimed.2019.112633>.
- Department of Statistics of Malaysia, 2017. *Abridged Life Tables (2015-2017)*. Department of Statistics of Malaysia, Putrajaya. Technical Report.
- Dhonde, S., Minoiu, C., 2013. Global poverty estimates: a sensitivity analysis. *World Dev.* 44, 1–13. <https://www.sciencedirect.com/science/article/pii/S0305750X1200304X>.
- Elvidge, C.D., Baugh, K.E., Kihn, E.A., Kroehl, H.W., Davis, E.R., Davis, C.W., 1997. Relation between satellite observed visible-near infrared emissions, population, economic activity and electric power consumption. *Int. J. Rem. Sens.* 18, 1373–1379. <https://doi.org/10.1080/014311697218485> doi:10.1080/014311697218485.
- Flood, D., Seiglie, J.A., Dunn, M., Tschida, S., Theilmann, M., Marcus, M.E., Brian, G., Norov, B., Mayige, M.T., Gurung, M.S., Aryal, K.K., Labadarios, D., Dorobantu, M., Silver, B.K., Bovet, P., Jorgensen, J.M., Guwatudde, D., Houehanou, C., AndallBrereton, G., Quesnel-Crooks, S., Sturua, L., Farzadfar, F., Moghaddam, S.S., Atun, R., Vollmer, S., Barnighausen, T.W., Davies, J.I., Wexler, D.J., Geldsetzer, P., Rohloff, P., Ramirez-Zea, M., Heisler, M., Manne-Goehler, J., 2021. The state of diabetes treatment coverage in 55 low-income and middle-income countries: a cross-sectional study of nationally representative, individual-level data in 680 102 adults. *The Lancet Healthy Longevity* 2, e340–e351. [https://doi.org/10.1016/S2666-7568\(21\)00089-1](https://doi.org/10.1016/S2666-7568(21)00089-1).
- Foster, J.E., 1998. Absolute versus Relative Poverty, vol. 88. *The American Economic Review*, pp. 335–341. URL: <http://www.jstor.org/stable/116944>.
- Foster, J., Greer, J., Thorbecke, E., 1984. A class of decomposable poverty measures. *Econometrica* 52, 761–766.
- Foster, J., Greer, J., Thorbecke, E., 2010. The Foster-Greer-Thorbecke (FGT) poverty measures: 25 years later. *J. Econ. Inequal.* 8, 491–524. <https://doi.org/10.1007/s10888010-9136-1>.
- Foster, J., Seth, S., Lokshin, M., Sajaia, Z., 2013. A Unified Approach to Measuring Poverty and Inequality—Theory and Practice : Streamlined Analysis with ADePT Software. A Unified Approach to Measuring Poverty and Inequality. <https://openknowledge.worldbank.org/handle/10986/13731>. doi:10.1596/978-0-8213-8461-9.
- Haughton, J., Khandker, S.R., 2009. *World Bank*, Washington, DC. <https://openknowledge.worldbank.org/handle/10986/11985>. doi:10.1596/9780-8213-7613-3.

- Hill-Briggs, F., Adler, N.E., Berkowitz, S.A., Chin, M.H., Gary-Webb, T.L., NavasAcien, A., Thornton, P.L., Haire-Joshu, D., 2020. Social determinants of health and diabetes: a scientific review. *Diabetes Care* 44, 258–279. <https://doi.org/10.2337/dci20-0053> doi:10.2337/dci20-0053.
- Howe, H.L., Wingo, P.A., Thun, M.J., Ries, L.A.G., Rosenberg, H.M., Feigal, E.G., Edwards, B.K., 2001. Annual report to the nation on the status of cancer (1973 through 1998), featuring cancers with recent increasing trends. *JNCI: J. Natl. Cancer Inst.* 93, 824–842. <https://doi.org/10.1093/jnci/93.11.824> doi:10.1093/jnci/93.11.824.
- Hsu, C.C., Lee, C.H., Wahlqvist, M.L., Huang, H.L., Chang, H.Y., Chen, L., Shih, S.F., Shin, S.J., Tsai, W.C., Chen, T., Huang, C.T., Cheng, J.S., 2012. Poverty increases type 2 diabetes incidence and inequality of care despite universal health coverage. *Diabetes Care* 35, 2286–2292. <https://doi.org/10.2337/dc11-2052>.
- Hua, X., Lung, T.W.C., Woodward, M., Salomon, J.A., Hamet, P., Harrap, S.B., Mancina, G., Poulter, N., Chalmers, J., Clarke, P.M., 2020. Self-rated health scores predict mortality among people with type 2 diabetes differently across three different country groupings: findings from the ADVANCE and ADVANCE-ON trials. *Diabet. Med. : a journal of the British Diabetic Association* 37, 1379–1385. <https://doi.org/10.1111/dme.14237>.
- Institute for Public Health (IPH), National Institutes of Health, Ministry of Health Malaysia, 2020. *National Health and Morbidity Survey (NHMS) 2019: Vol. I: NCDs—Non-Communicable Diseases: Risk Factors and Other Health Problems (Technical Report)*.
- Jiang, P., Babazono, A., Fujita, T., 2020. Health inequalities among elderly type 2 diabetes mellitus patients in Japan. *Popul. Health Manag.* 23, 264–270. <https://doi.org/10.1089/pop.2019.0141>.
- Marcus, M.E., Manne-Goebler, J., Theilmann, M., Farzadfar, F., Moghaddam, S.S., Keykhaei, M., Hajebi, A., Tschida, S., Lemp, J.M., Aryal, K.K., Dunn, M., Houehanou, C., Bahendeka, S., Rohloff, P., Atun, R., Bärnighausen, T.W., Geldsetzer, P., Ramirez-Zea, M., Chopra, V., Heisler, M., Davies, J.I., Huffman, M.D., Vollmer, S., Flood, D., 2022. Use of statins for the prevention of cardiovascular disease in 41 low-income and middle-income countries: a cross-sectional study of nationally representative, individual-level data. *Lancet Global Health* 10, e369–e379. [https://doi.org/10.1016/S2214-109X\(21\)00551-9](https://doi.org/10.1016/S2214-109X(21)00551-9) doi:10.1016/S2214109X(21)00551-9.
- Mariapun, J., Hairi, N.N., Ng, C.W., 2016. Are the poor dying younger in Malaysia? An examination of the socioeconomic gradient in mortality. *PLoS One* 11, 1–12. <https://doi.org/10.1371/journal.pone.0158685> doi:10.1371/journal.pone.0158685.
- Meo, S.A., Memon, A.N., Sheikh, S.A., Rouq, F.A., Usmani, A.M., Hassan, A., Arian, S.A., 2015. Effect of environmental air pollution on type 2 diabetes mellitus. *Eur. Rev. Med. Pharmacol. Sci.* 19, 123–128.
- Ministry of Health Malaysia, 2020. *National Diabetes Registry Report 2013-2019*.
- Ministry of Health Malaysia, 2021. *National Diabetes Registry Report 2020*.
- Minioiu, C., Reddy, S.G., 2008. Estimating poverty and inequality from grouped data : how well do parametric methods perform? *J. Income Distrib.* 18, 1–24.
- Mirza, M.U., Xu, C., van Bavel, B., van Nes, E.H., Scheffer, M., 2021. Global inequality remotely sensed. *Proc. Natl. Acad. Sci. USA* 118, e1919913118. <https://doi.org/10.1073/pnas.1919913118> doi:10.1073/pnas.1919913118.
- National Centers for Environmental Information- NCEI, 2013. *Global DMSPOLS Nighttime Lights Time Series 1992 (Version 4)*. URL: <https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html>.
- NCD Risk Factor Collaboration (NCD-RisC), 2016. Worldwide trends in diabetes since 1980: a pooled analysis of 751 population-based studies with 4.4 million participants. *Lancet (London, England)* 387, 1513–1530. [https://doi.org/10.1016/S0140-6736\(16\)00618-8](https://doi.org/10.1016/S0140-6736(16)00618-8).
- Pradeepa, R., Prabhakaran, D., Mohan, V., 2012. Emerging economies and diabetes and cardiovascular disease. *Diabetes Technol. Therapeut.* 14 <https://doi.org/10.1089/dia.2012.0065>.
- Ramachandran, A., Ma, R.C.W., Snehalatha, C., 2010. Diabetes in Asia. *Lancet (London, England)* TA - TT - 375, 408–418. [https://doi.org/10.1016/S0140-6736\(09\)60937-5](https://doi.org/10.1016/S0140-6736(09)60937-5) <https://eur.on.worldcat.org/oclc/587479527>.
- Ravallion, M., 2020. On measuring global poverty. *Annual Review of Economics* 12, 167–188. <https://doi.org/10.1146/annurev-economics-081919-022924> doi: 10.1146/annurev-economics-081919-022924.
- Sankaranarayanan, R., Swaminathan, R., Brenner, H., Chen, K., Chia, K.S., Chen, J.G., Law, S.C.K., Ahn, Y.O., Xiang, Y.B., Yeole, B.B., Shin, H.R., Shanta, V., Woo, Z.H., Martin, N., Sumitsawan, Y., Sriplung, H., Barboza, A.O., Eser, S., Nene, B.M., Suwanrungruang, K., Jayalekshmi, P., Dikshit, R., Wabinga, H., Esteban, D.B., Laudico, A., Bhurgri, Y., Bah, E., Al-Hamdan, N., 2010. Cancer survival in Africa, Asia, and Central America: a population-based study. *Lancet Oncol.* 11, 165–173. [https://doi.org/10.1016/S1470-2045\(09\)70335-3](https://doi.org/10.1016/S1470-2045(09)70335-3).
- Smajlović, D., Kojić, B., Sinanović, O., 2006. Five-year survival-after first-ever stroke. *Bosn. J. Basic Med. Sci.* 6, 17–22. <https://doi.org/10.17305/bjbm.2006.3138>.
- The Bypass Angioplasty Revascularization Investigation (BARI), 1997. Influence of diabetes on 5-year mortality and morbidity in a randomized trial comparing CABG and PTCA in patients with multivessel disease. *Circulation* 96, 1761–1769. <https://doi.org/10.1161/01.CIR.96.6.1761> doi:10.1161/01.CIR.96.6.1761.
- The Poverty Line. *J. Econ. Surv.* 5, 243–261. URL: <https://doi.org/10.1111/j.1467-6419.1991.tb00134.x>, doi:https://doi.org/10.1111/j.1467-6419.1991.tb00134.x.
- Times of India, 2021. Five-year Survival Rate: what Is it and Everything You Need to Know about it. URL: <https://m.timesofindia.com/life-style/health-fitness/health-news/five-year-survival-rate-what-is-it-and-everything-you-need-to-know-about-it/photostory/81778210.cms>.
- Verdecchia, A., Francisci, S., Brenner, H., Gatta, G., Micheli, A., Mangone, L., Kunkler, I., 2007. Recent cancer survival in Europe: a 2000–02 period analysis of EUROCARE-4 data. *Lancet Oncol.* 8, 784–796. URL: <https://www.sciencedirect.com/science/article/pii/S1470204507702462>.
- Wagstaff, A., Van Doorslaer, E., Watanabe, N., 2001. On Decomposing the Causes of Health Sector Inequalities with an Application to Malnutrition Inequalities in Vietnam. *Policy Research Working Paper*. World Bank, Washington, DC, p. 2714. URL: <https://openknowledge.worldbank.org/handle/10986/19426>.
- Zhang, P., Zhang, X., Brown, J., Vistisen, D., Sicree, R., Shaw, J., Nichols, G., 2010. Global healthcare expenditure on diabetes for 2010 and 2030. *Diabetes Res. Clin. Pract.* 87, 293–301. <https://doi.org/10.1016/j.diabres.2010.01.026>.