Human Capital and Institutions in Health:

Evidence on Outcomes and Behaviours

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A Introduction

A.1 Motivation

Health outcomes and health-related behaviours vary markedly across and within countries globally. Some populations achieve long, healthy lives, while others continue to face enduring disadvantages in health, development, and survival. These disparities represent one of the most pressing challenges in contemporary public health and economics research (Dopelt, 2025; Rad, 2025; World Health Organisation [WHO], 2018). Health is both a fundamental component of human wellbeing and a central driver of economic development (WHO, 2023a). Differences in population health reflect more than biological or environmental conditions; they emerge from forces shaped by human capital formation, institutional quality, and the incentives that govern individual and collective behaviour (Patton-López, 2022; Orille et al.,2024). Poor health perpetuates cycles of poverty by reducing productive capacity, limiting educational attainment, and constraining economic growth (Fu et al., 2024; Fumagalli et al., 2024).

Even with advances in public health interventions and international development efforts, some populations continue to experience poor health outcomes and limited physical development (WHO, 2025). Sub-Saharan Africa (SSA), in particular, continues to bear a disproportionate burden of preventable diseases and mortality (Vos et al., 2020; WHO Regional Office for Africa, 2023), although variation in disease burden characterises populations globally. High disease burdens create direct costs associated with treatment and care provision, as well as indirect costs arising from reduced workforce productivity and diverted resources from other developmental priorities (Mobosi et al., 2023; Sachs & Malaney, 2002). The COVID-19 pandemic highlighted how health vulnerabilities can quickly lead to economic and social disruption worldwide (McKee & Stuckler, 2020; Shadmi et al., 2020). Understanding the drivers of health variations and the structural forces that shape long-term health outcomes is important for achieving the health-related Sustainable Development Goals (Acharya et al., 2018). This dissertation investigates how human capital at multiple levels, institutions and health-related knowledge shape health outcomes and behaviours, with a particular focus on the malaria burden, life expectancy, height inequality, and behavioural responses to malaria prevention and treatment. It demonstrates that health outcomes and behaviours are shaped by present and past conditions and their interaction.

A.2 Health Outcomes: Dimensions and Measurement

The studies in this dissertation examine health by focusing on three outcomes: malaria burden, life expectancy, and height inequality.

A.2.1 Malaria Burden

Malaria burden refers to the morbidity, mortality and socioeconomic consequences of malaria infection at the population level, typically measured through prevalence and mortality statistics. It is one of the most significant public health challenges in Sub-Saharan Africa (SSA), accounting for approximately 95 per cent of global malaria cases and 96 per cent of malaria deaths (WHO, 2023b, 2024). There are substantial variations in malaria burden across countries in SSA: The North Africa region and most South African countries have near-zero prevalence, while Nigeria, the Democratic Republic of Congo, and Uganda continue to experience high transmission, accounting for nearly half of global malaria cases. The disease burden reflects not only the biological transmission dynamics of Plasmodium parasites but also broader individual behaviours, socioeconomic and institutional conditions that determine exposure, prevention practices, and access to treatment (WHO, 2023b, 2024).

Malaria prevalence and mortality serve as key indicators of disease burden, reflecting both disease transmission intensity and the effectiveness of control efforts (Mezieobi et al., 2025; Snow et al., 2005). While environmental and climatic factors establish baseline transmission potential, variation in disease burden reflects differences in health system capacity, intervention coverage, population behaviours, and access to prevention (Apeagyei et al., 2024; Bhatt et al., 2015; Feachem et al., 2019; Mills, 2014). The economic consequences of malaria extend beyond immediate health costs, affecting labour productivity, educational attainment, and long-term economic development (Bleakley & Lange, 2009; Patouillard et al., 2023).

A.2.2 Life Expectancy

Life expectancy represents a summary measure of population health that captures the cumulative effect of mortality risks across the entire lifespan (Davies et al., 2025). It reflects not only healthcare access and quality but also broader determinants, including education, nutrition, sanitation, income, and social conditions (Aytemiz et al., 2024). Life expectancy has increased globally over the past two centuries, from about 30 years in the 1800s to more than 70 years today, due to improvements in nutrition, sanitation, medical care, and public health infrastructure (Oeppen & Vaupel, 2002). Despite this progress, large differences remain, with life expectancy in some SSA countries still below 60 years (Kyriacou et al., 2025; Mejía-Guevara et al., 2025). These disparities across countries and regions reflect differences and interactions in health system capacity, human capital, exposure to infectious diseases, socioeconomic development, and institutional quality (Aksan & Chakraborty, 2023; Galvani-Townsend et al., 2022; Zheng & Canudas-Romo, 2024).

A.2.3 Height Inequality

Height inequality refers to the dispersion of adult height within populations, typically measured through the coefficient of variation or standard deviation of height distributions. Adult height represents a biological marker of cumulative nutritional and health conditions experienced during childhood and adolescence (Steckel, 1995, 2009). Because height is determined by the interaction between genetic potential and environmental conditions, including nutrition, disease exposure, and access to healthcare during critical growth periods (Silventoinen, 2003), variation in population height captures inequalities in early-life conditions. Height inequality, therefore, serves as a biological marker of developmental disparities within societies (Floud et al., 2011; Moradi & Baten, 2005). This measure has proven particularly valuable and has been widely used in economic history to trace changes in living standards and inequality (Baten & Blum, 2012, 2014).

A.3 Health Behaviours

Beyond health outcomes, this dissertation examines the behaviours that shape these outcomes, specifically malaria prevention and control practices. Health behaviours refer to the actions individuals take to maintain, restore, or improve their health, and they constitute critical pathways through which social, economic and institutional determinants translate into health outcomes (Gardner et al., 2023; Cockerham, 2005). In the context of malaria, preventive behaviours include the use of insecticide-treated bed nets, clearing mosquito breeding grounds, indoor residual spraying, prompt treatment-seeking for fever, and adherence to preventive medications during pregnancy (Dhiman, 2009; Monroe et al., 2021). Health knowledge, economic resources, government policies, cultural beliefs, and access to health services shape these behaviours. Understanding what drives malaria prevention behaviours is key to explaining why populations exposed to similar disease risks may experience very different health outcomes.

A.4 Human Capital and Institutions in Health

A.4.1 Human Capital and Health

Human capital encompasses the knowledge, skills, and capabilities individuals possess (World Bank, 2019). It is central to understanding economic development and social well-being. Human capital formation describes the broader process through which individuals acquire knowledge, skills, and competencies that enhance their productive capacity (Hanushek & Woessmann, 2008; Pelinescu, 2015). It includes formal education systems, informal learning processes, and experiential knowledge acquisition (OECD, n.d.). Education is the main measurable form of human capital, as formal attainment provides systematic, comparable measures across populations and time. In health contexts, human capital includes not only general education but also health-specific competencies, such as health literacy and numeracy, which enable effective engagement with health systems and the adoption of preventive behaviours (Baker, 2006; Golbeck et al., 2005; Nutbeam, 2008). This section examines how human capital shapes health outcomes and health behaviours, beginning with theoretical frameworks and followed by empirical evidence from historical and contemporary contexts.

Theoretical foundations

The human capital theory, articulated by Schultz (1961) and refined by Becker (1964), posits that investments in education enhance individuals' productive capabilities and decision-making capacity. Applied to health, this theory suggests that educational investments improve health outcomes by increasing health knowledge, promoting more efficient use of medical resources, fostering future-oriented behaviour, and expanding economic resources that support access to healthcare and healthier living conditions.

Grossman's (1972, 2000, 2017) health capital model builds on this framework by conceptualising health as both a consumption good, providing direct utility and an investment good, determining the time available for productive activities. Education enhances individual productive capacity not only for economic activities but also for health production. Educated individuals can produce health more efficiently with given inputs and allocate resources more effectively across health investments (Hahn & Truman, 2015). Recent extensions of the Grossman model incorporate endogenous demand for knowledge capital, recognising that health and education investments are jointly determined throughout the life course rather than acquired sequentially (Chen, 2024). Together, these theoretical foundations demonstrate that human capital is central to shaping health outcomes.

Historical persistence and development

Economic history shows that human capital has long-term persistence and enduring effects on development and health outcomes (Nunn, 2009; Spolaore & Wacziarg, 2013). Historical investments in education created path dependencies through the intergenerational transmission of skills, the development of supporting institutions, and the accumulation of collective knowledge, all of which facilitated innovation (Squicciarini & Voigtländer, 2015). Elite human capital, the skills and knowledge of rulers, religious leaders, merchants, and administrators, played a particularly important role in historical development (Baten & Alexopoulou, 2022; Baten & Keywood, 2019). The colonial period in SSA created lasting inequalities in educational and health infrastructure, with contemporary health outcomes reflecting these historical patterns (Huillery, 2009). Colonial administrations in Africa relied heavily on educated elites for implementing public health programs, including disease surveillance, vaccination campaigns, and sanitation infrastructure (Patterson, 1981). Regions with higher elite human capital were able to develop health institutions and adopt new medical technologies and public health practices (Bolt & Bezemer, 2009). Historical human capital has been shown to correlate with subsequent economic development, institutional quality, and technological adoption (Amsden et al., 2012; Crayen & Baten, 2010).

Mechanisms and contemporary evidence

Evidence shows that higher educational attainment is associated with better health outcomes, including lower mortality, reduced disease incidence, improved preventive behaviours, and greater subjective well-being (Balaj et al., 2024; Zajacova & Lawrence, 2018). Education equips individuals with knowledge, economic resources, and decision-making capacity that support healthier lives (Cerf, 2023). The effect of education on health operates through multiple pathways across different levels of social organisation, which often interact to influence health outcomes (Solar & Irwin, 2010). At the individual level, education affects health through several mechanisms. It develops knowledge and cognitive skills that enable better health decision-making and information processing (Karran et al., 2023). It generates economic resources that facilitate access to healthcare, healthier living conditions, and preventive measures (Lindberg et al., 2022). Education also provides social and psychological resources, such as self-efficacy and social networks that reinforce health behaviours. Additionally, it may shape time preferences, risk perceptions and planning, influencing preventive behaviours and navigation of healthcare systems (Gupta & Rudisill, 2024; Lawless et al., 2013; Van Der Pol, 2011). Individuals with higher education are more likely to seek early treatment, adhere to disease prevention measures, participate in vaccination programs, and engage in health-promoting behaviours.

At the community level, education creates spillover effects. Collective knowledge supports local health initiatives, establishes social norms around health behaviours, and promotes civic participation that strengthens public health investment. Social learning and peer influence affect preventive behaviours such as vaccination uptake, bed net use, and treatment adherence (Cutler & Lleras-Muney, 2010). Regions with higher average education levels demonstrate faster adoption of public health innovations and stronger responses to health crises. For instance, during the COVID-19 pandemic, communities with higher educational attainment showed greater compliance with preventive measures and higher vaccine uptake (Bergen et al., 2021; Karp et al., 2025). At the societal and global levels, human capital shapes the quality of the health system, institutional capacity, and technological innovation (Wang & Lu, 2022). Education among healthcare workers is linked to hospital quality, patient safety, and the implementation of quality improvement initiatives (Aiken et al., 2014). Countries with stronger educational systems develop more effective public health infrastructure, adopt medical innovations more rapidly, and respond more efficiently to disease outbreaks. Education also contributes to global health governance by training professionals, fostering scientific expertise, and shaping policymakers who influence cross-border health initiatives.

Central to education's effects on health are health literacy and numeracy, which enable individuals to access, understand, interpret, and apply health information effectively. Health literacy encompasses reading comprehension, communication skills, and navigation of healthcare systems, while numeracy enables individuals to interpret quantitative health information, assess disease risks, and follow treatment protocols (Nutbeam, 2008; Reading Turchioe & Mangal, 2024; Reyna et al., 2009). Research demonstrates that higher levels of health literacy and numeracy are associated with improved medication adherence, preventive care utilisation, disease management, and engagement with public health campaigns (Berkman et al., 2011; Dahm et al., 2023; Nelson et al., 2008). These competencies are important for addressing infectious diseases like malaria, enabling individuals to make informed decisions about prevention, treatment, and participation in community health initiatives. Overall, human capital shapes health outcomes and behaviours through interconnected individual, community, and societal mechanisms, with effects that are both immediate and cumulative over time.

A.4.2 Institutions and Health

Institutions are formal and informal rules that structure social, economic, and political interactions and fundamentally shape health outcomes by influencing resource allocation, service delivery, and collective action (Acemoglu & Robinson, 2013; North, 1990).

Institutions affect health by creating accountability mechanisms that incentivise governments to provide public health services (Kudamatsu, 2012). Governance quality is particularly important in low-income countries, where weak institutions often result in ineffective health systems, corruption, and inadequate public health infrastructure (Banik et al., 2023; George et al., 2023; Rahman et al., 2025). Cross-country research showed that better governance is associated with lower infant mortality, higher life expectancy, and better health system performance (Khatri et al., 2025; Kouadio & Njong Mom, 2025).

Institutional quality influences not only the availability of resources but also the effectiveness and management of health investments. Countries with strong regulatory and accountability structures achieve higher service quality and better population health outcomes, while weak institutions reduce trust, create inefficiencies, and limit access to adequate care (Acemoglu & Robinson, 2013). Strong governance also improves the absorption and utilisation of external health funds, increasing returns in service readiness and population outcomes (Dieleman et al., 2014). This evidence indicates that institutional strength supports health system improvements across countries and helps ensure that available resources, including external assistance, are used effectively.

A.5 Outline of the Dissertation

This dissertation analyses how human capital and institutions shape health outcomes and behaviours in SSA and globally. The first study in Chapter B investigates whether regional elite numeracy, a proxy for human capital, affects long-term health outcomes, focusing on malaria prevalence and life expectancy. Using subnational data, the study finds that regions with historically higher elite numeracy exhibit better current health outcomes. The second study in Chapter C validates measures of health numeracy and literacy and explores how they influence malaria control behaviours at the individual level using data from a cross-sectional survey conducted in Gabon. It analyses their direct associations with key malaria preventive behaviours, including insecticide-treated net use, indoor spraying, bush clearance, timely treatment-seeking, and treatment adherence. The study finds that both numeracy and literacy independently and positively associate with preventive practices. Health literacy mainly supports preventive behaviours and dosing knowledge, while health numeracy informs treatment-seeking decisions. Both competencies are necessary for treatment adherence and effective communication with healthcare providers.

The third study, presented in Chapter D, examines how institutional quality and development assistance for health interact with domestic health worker density to influence malaria cases and deaths in SSA. Using panel data from 38 SSA countries between 2010 and 2022, the study finds significant spatial clustering of the malaria burden. Overall, the malaria burden has declined across the region, though some areas continue to experience high prevalence and mortality. Interventions such as insecticide-treated net access and antenatal care coverage are associated with reductions in cases and deaths, while higher health worker density, development assistance, and government effectiveness are positively associated with local malaria burden. Local factors, rather than cross-border influences, predominantly shape malaria patterns. Regional resource availability shows some spillover benefits, suggesting that effective malaria control requires both strengthened local health systems and strategic regional coordination that accounts for spatial patterns in service coverage and environmental risk. The fourth and final study in Chapter E examines how implementing compulsory education policies shapes patterns of global health inequality. Using a dataset of over 60 countries from 1810 to 2000 and employing height inequality as a health indicator, it applies Difference-in-Differences estimation. The findings indicate that compulsory education reduces height inequality over time, suggesting that education contributes to redistributing health outcomes across populations.

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B Regional Elite Numeracy Formation in Sub-Saharan Africa during the 17th to 19th Century and its Path-Dependent Relationship with Today's Health Outcomes[1]

Abstract

Is there a relationship between early elite numeracy and today's health outcomes in Sub-Saharan Africa? Using subnational data from 44 countries, we find that regions with higher elite numeracy during the 17th to 19th centuries now have higher life expectancy and lower malaria prevalence. We employ an instrumental variable approach utilising proximity to historical centre as an exogenous source of variation in elite numeracy diffusion. We supplement this with robustness checks that control for African-region fixed effects, numeracy levels today, and the choice of century. The relationship persists even after including historical, geographical, and contemporary covariates, including GNI per capita, slavery intensity, colonial infrastructure, historical population density, coastal proximity, natural resource endowments, and current population distribution. To isolate the effect of European influence in the relationship, we examine the effect of colonial missions, and our findings suggest that African elite numeracy formation still plays a crucial role. We investigate the various channels of path dependence and find that elite numeracy has a persistent and independent relationship with current health outcomes, although early numeracy patterns did not entirely predetermine regional health differences.

[1] This chapter is based on a forthcoming article by Namubiru and Baten (2026), in the Journal of Development Studies. The version included in this dissertation is identical in content, with only minor textual differences. I contributed approximately 80 percent to this paper.

B.1 Introduction

The historical performance of institutional development and human capital formation demonstrates persistent effects on contemporary development outcomes. Human capital investments are important for societal and individual growth and development (Becker, 1962; Gennaioli et al., 2013). There is a relationship between human capital, including early human capital and broader development outcomes such as contemporary educational attainment, economic growth, and institutional quality (Hanushek & Woessmann, 2008; Huggins et al., 2021; Squicciarini & Voigtländer, 2015). The historical distribution of human capital has received increasing attention in recent years. Various studies have shown that human capital formation among elites contributes to national development (Baten & Alexopoulou, 2022; Keywood & Baten, 2021). Early investments in cognitive skills are important for shaping long-term paths of institutional quality, socioeconomic progress, and public service provision (Crayen & Baten, 2010; Becker et al., 2011; Glaeser et al., 2004; Squicciarini & Voigtländer, 2015).

Population health represents a fundamental dimension of development that captures the cumulative effects of economic, social, and institutional conditions (Deaton, 2013; Fogel, 2004). There exist recognised interconnections between historical human capital accumulation and population health outcomes (Cutler et al., 2006; Lleras-Muney, 2005); however, the specific role of historical human capital accumulation and its influence on present-day health outcomes has received relatively little attention. Many studies rely on colonial-era education measures or missionary school attendance, but our approach captures indigenous traditions of numerical precision that developed mostly independently of external interventions. Huillery (2009) demonstrated that regions that received greater colonial investments in education and health today maintain higher levels of education and health performance. Higher human capital in earlier centuries led to the development of bureaucratic structures capable of implementing effective health interventions, public education, and disease control mechanisms (Cutler et al., 2006; Becker et al., 2011).

Health occupies a unique position in development theory, as it is both an outcome and an input into the development process. Unlike purely economic indicators such as income or consumption, health represents fundamental human capital that enables participation in economic, social, and political activities. Improvements in health affect income by making human capital more productive, establishing health as a fundamental component of productive capacity rather than merely a consumption good (Bleakley, 2010). Health outcomes serve as diagnostic indicators of underlying structural inequities and the persistence of historical disadvantages within societies (Bleakley, 2010; Deaton, 2013). Health outcomes such as life expectancy, child mortality, and disease prevalence serve not only as reflections of individual and population health status but also as key indicators of the broader developmental environment, as they summarise long-term effects of investments in education, governance, infrastructure, and public health systems (Bloom et al., 2004). They are emphasised by global institutions such as the World Health Organisation (WHO) and United Nations Development Programme (UNDP) as core indicators of well-being and equity (WHO, 2021; UNDP, 2024).

Healthy life expectancy varies considerably across Africa, with the regional average reaching 56 years in 2019, though significant variations remain between countries (WHO Regional Office for Africa, 2018; 2022). The malaria prevalence rate in Sub-Saharan Africa per 1000 population varies widely across regions (WHO, 2020). Most South African countries have near-zero prevalence, while Nigeria, the Democratic Republic of Congo and Uganda continue to experience high transmission. Various contemporary factors such as education, income, improved healthcare, public policies, societal and governance structures, improved disease control behaviours, medical funding and research, and increased access to medical services explain these variations and influence health outcomes (Ashraf et al., 2009; Garrido-Vergara & Sepúlveda-Rodríguez, 2023; Lena & London, 1993; Lin, et al, 2012; Monsef, & Mehrjardi, 2015; Powles, 2001; Taylor et al., 2016; WHO, 2020).

This study seeks to provide new evidence on the numeracy levels of African elites in the 17th, 18th and 19th centuries and their influence on modern-day health outcomes. We extend the current literature based on indicators developed by Baten & Alexopoulou (2022) to construct measures of elite numeracy. Elite numeracy, measured through numeracy estimates of societal elites (Baten & Alexopoulou, 2022; Keywood & Baten, 2021), provides a proxy for historical human capital necessary for regional development (Crayen & Baten, 2010). Our study focuses on life expectancy and malaria prevalence as key health outcomes. To understand the relationship between elite numeracy and health outcomes today, we draw on Becker's (1975) human capital theory, which holds that education and skills contribute to economic productivity and long-term growth. David (1985, 2007) and Arthur (1989) emphasise that historical characteristics are important in economic analysis based on the path dependency theory.

Their established validity methodologically justifies selecting life expectancy and malaria prevalence as comprehensive population health measures (Murray & Lopez, 1997; Stiefel et al., 2010; WHO, n.d.) and as policy-relevant for understanding long-term development trajectories (Preston, 1975). These indicators have been widely used in studies assessing the long-term impact of colonial and pre-colonial legacies in Africa (Alsan, 2015). The quality and accessibility of health services, public health infrastructure, and individual health behaviours are outcomes that rely on governance, planning, and human capital, all of which are conditioned by cognitive capacity. Our research contributes by examining elite numeracy as historical human capital with relevance for health outcomes.

We assess the following hypotheses in our study:

Hypothesis I: Higher historical numeracy is associated with better health and longevity because higher elite numeracy might move a region onto a higher welfare path due to investments in more public goods and a stronger emphasis on overall education.

Hypothesis II: Higher levels of elite numeracy are associated with lower malaria prevalence. Early elite numeracy might have translated into later general numeracy; hence, higher numeracy might be associated with lower malaria prevalence.

Besides human capital, historical institutions, cultural factors, geography, the slave trade, colonial legacies, and politics also explain long-term economic development patterns (Acemoglu et al, 2002, 2003; Acemoglu & Robinson, 2012; Mokyr, 2016; Nunn, 2008, 2009; Robinson, 2013; Rodríguez-Pose, 2013). Better pre-colonial institutions are associated with higher levels of education, health, and infrastructure in African countries today (Gennaioli & Rainer, 2007; Michalopoulos & Papaioannou, 2013a, 2013b). Communities that were more exposed to historical slave trading exhibit lower levels of interpersonal trust, which suggests that historical disruptions created cultural orientations that may continue to impede human capital formation (Nunn, 2009; Nunn and Wantchekon, 2011). Whatley and Gillezeau (2011) show that slave trade exposure weakened traditional political authority and increased ethnic heterogeneity, thereby reducing the capacity for collective action necessary for educational investments. The quality of institutions during the colonial period and mission activities, including legal systems, social capital, public sector efficiency, taxation, and governance structures, were critical factors in economic growth and development (Acemoglu et al., 2002, 2005; Acemoglu & Robinson, 2012; Austin, 2008).

Missionary activities across Africa had substantial long-run positive effects on contemporary educational attainment, though the impacts varied by gender (Nunn, 2014). Cagé and Rueda (2016) in their study find a positive relationship between the existence of missions with or near a printing press and indicators of social capital, such as trust and education. In Nigeria, historical missionary activity has had a persistent effect on schooling outcomes, though it contributed to a reversal of fortunes with historically richer ethnic groups being poorer today (Okoye & Pongou, 2014). Empirical evidence from Benin showed that access to colonial-era educational benefits was restricted to ruling lineages, with limited trickle-down effects (Wantchekon et al, 2015). Colonial legal diversity, while preserving some traditional institutions, created fragmented authority structures that complicated the provision of public goods (Lange, 2004). Our study will isolate the specific contribution of historical elite numeracy to contemporary health outcomes while accounting for these alternative factors.

B.2 Materials and Methods

We assessed the hypotheses at the sub-national regional level (Administrative level 1 for each country in the study) across 44 countries in Sub-Saharan Africa.

B.2.1 Outcome Variables

The primary outcome variables are contemporary health outcomes, measured as average life expectancy from 2000 to 2019, and malaria prevalence averaged from 2010 to 2020. This data has been averaged to smooth out any short-term variations and capture sustained health. Life expectancy is sourced from the Subnational HDI Database of the Global Data Lab (Smits & Permanyer, 2019). Life expectancy is measured as the life expectancy at birth. Malaria prevalence data is sourced from the Malaria Atlas project database, and it is assessed as the proportion of children 2 to 10 years with malaria infection in a defined year (defined as a rate per 100 children).

Generally, average life expectancy stands at 56.95 years, and malaria prevalence is 18.21 per cent, with a variation of 14.82 per cent, indicating differences in malaria prevalence (Table B.8 in the appendix). Life expectancy also varies substantially across regions (Figure B.1). It tends to be higher in some regions of the Northeast (including some regions of Ethiopia), Madagascar, and the West, such as Senegal. Western and Central Africa are the regions most affected by malaria (Figure B.2). The highest prevalence of malaria is experienced in regions of Nigeria and Burkina Faso in Western Africa and the Democratic Republic of the Congo and Cameroon in Central Africa. Eastern Africa exhibits lower malaria prevalence rates than Central and Western Africa, though some regions of Uganda stand out for their high levels. Malaria prevalence is generally lower in Southern Africa compared to other regions of the continent, though certain areas, such as parts of Mozambique and Zimbabwe, still experience high malaria prevalence rates.

B.2.2 Independent Variable

As a measurement strategy for this study, we estimate elite numeracy as a historical indicator of human capital using a new proxy strategy (Keywood & Baten, 2021; Baten & Alexopoulou, 2022). We estimated elite numeracy from the 17th to the 19th centuries. This indicator is based on the share of known birth years of rulers. In ruler lists, the beginning and end of a rule are often noted. However, the biographical detail of the ruler's birth year is only given if the bureaucracy around the ruler had sufficient numerical skills. In other words, rulers for whom accurate birth year information was reported were more likely to have been part of a society that valued numeracy skills and had the means to record and transmit this information accurately. It does not necessarily measure the numeracy of the ruler himself but, rather, that of the governmental and bureaucratic elite around him and, by implication, that of the elites of the country in general. This, therefore, provides estimates of numeracy skills among elites across different countries, regions, and periods. Keywood and Baten (2021) found a strong correlation between this "ruler birth year known" variable and other early educational indicators, such as the number of monastery manuscripts per capita. Similarly, Baten & Alexopoulou (2022) found a strong correlation of 0.66 ($p = 0.0136$) between 18th-century elite numeracy and overall 18th-century numeracy at the regional level, covering areas as large as modern countries. They also found a correlation of 0.60 ($p = 0.0113$) at the country level for the 19th century. Hence, the share of known birth years can be empirically shown to serve as a valid indicator of early elite numeracy.

Data sources include biographical works, with Truhart's (1984) list of rulers serving as a primary reference, as it provides the greatest number of sources. We show a snapshot of Truhart's work. For example, the ruler Nabingali, who ruled from 1830 to 1860 in the principality of Monbuttu in modern-day Democratic Republic of Congo, is known to have been born in 1810. However, the birth year for Mebula, who ruled between 1710 and 1761, is unknown (see Appendix, Table B.10). Data is available for all rulers, even when their polities were relatively small. We did not include European rulers or governors, or post-colonial presidents and ministers, but we did include the Arabic-origin dynasties on the east coast, as these often became "local dynasties" soon after arrival.

All potential biases of the "ruler birth known" indicator have been extensively discussed by Baten & Alexopoulou (2022). These include university system quality effects, though England had fewer known birth years compared to Iraq in the Middle Ages (Baten et al., 2021), and Russia exhibited lower elite numeracy than Imperial Abyssinia in the 16th century (see appendix, Figure B.10). Archive destruction biases are countered by evidence of declining numeracy over time, such as after the 8th century (Keywood & Baten, 2021). Fame bias towards better-known rulers and cultural preferences against using numbers were tested and found not to influence significance. European contact effects were ruled out as inland regions in Niger, Botswana, Sudan and Uganda reported birth years before 1900, with high-elite numeracy values not constrained to early European contact regions (Figures B.3, B.4 and B.5). Strong correlation exists between elite and general numeracy (see appendix Figure B.9).

Looking at the overall variation, the Southern African region- including Madagascar- shows very high levels of elite numeracy (Figures B.3, B.4 and B.5) in all the centuries. Central and Western Africa had the lowest levels of elite numeracy in all the centuries. Apart from the latter territory of South Africa, several other regions had high elite numeracy already in the 17th and 18th centuries, such as the East Congo region, northern Ethiopia, northern Madagascar, Senegambia, and the Botswana-Zimbabwe region. In the 19th century, several individual regions of Central and West Africa were added to this, as well as regions in Angola and Botswana. Generally, East African values were slightly higher than average but far below the Southern region. In summary, substantial differences in elite numeracy across the African region existed.

B.2.3 Controls

We included several control variables categorised into historical, geographical, and contemporary to isolate the specific effect of elite numeracy on health outcomes. The historical controls are precolonial routes presence, population in the 1600s, Crop production estimates of the 17th century, slavery, and the presence of colonial railways. Geographical attributes are distance to the coast, latitude, the existence of a city now, and the presence of oil in the region. We also include contemporary variables such as GDP per capita, current years of schooling, and population density today. To account for varying ecological suitability for malaria transmission across regions in SSA, we included the Malaria Ecology Index in the analyses of malaria prevalence (Kiszewski et al., 2004). This accounts for the geographical heterogeneity across regions, with Southern Africa and parts of Eastern Africa experiencing very low or no malaria prevalence. The descriptive statistics and data sources of the variables are summarised in Tables B.8 and B.9 in the appendix, respectively.

B.2.4 Empirical Strategy

For our econometric analysis, we focused only on regions that had at least 10 rulers for elite numeracy. This gives a more comprehensive representation of variations in elite numeracy and reduces measurement error. Our baseline empirical specification examines the relationship between elite numeracy and contemporary health outcomes at the sub-national level based on the model:

$$Y_i = \beta X_{it} + CQ_t + \delta_t + V_q + \varepsilon_{it} \tag{1}$$

where Y_i is the health outcome measure for region i, X_{it} is the elite numeracy for region i in century t, Q_{it} is a vector of both time-variant and invariant region controls, δ_t is the time fixed effects represented by centuries, V_q are country-level fixed effects and finally, ε_{it} is the error term. This is a weighted OLS regression with robust standard errors to control for potential heteroskedasticity (White, 1980).

To address potential endogeneity concerns in estimating the causal effect of elite numeracy on contemporary life expectancy and malaria prevalence, we employed an instrumental variable (IV) approach. From a theoretical perspective, the direction of causality might not be questionable, as the earliest elite numeracy is from the 17th century, while the dependent variables are from the 21st century. However, autocorrelation across regions might exist; some high longevity regions may also have exhibited similar characteristics in the 17th century. Using the IV regression further helps address potential endogeneity arising from omitted-variable bias and measurement error. We use the distances from the historical centres of Timbuktu, Gao, Mutapa, and Ethiopia, as well as the distance to Southern Africa, composited into a single measure using Principal Component Analysis (PCA) as an instrument for historical elite numeracy levels. We leveraged on the historical writing precedence of these regions as well as trade connections. We assess our instrument for its exclusion criteria.

B.3 Results and Discussion

B.3.1 Baseline Regression Results

Multiple regression models are employed to examine the relationship between historical elite numeracy and contemporary life expectancy and malaria prevalence. Table B.1 shows the baseline regression results for life expectancy. The findings suggest that regions with higher elite numeracy are associated with longer life expectancies today. Columns 2, 3, and 4 show that the coefficient remains significant and positive, though it is reduced when contemporary, historical, and geographical factors are included in the model. Historical factors such as slavery and the presence of a colonial railway in the region are not associated with current life expectancy.

Table B.1: Effect of Elite Numeracy on Life Expectancy (2000-2019) using OLS estimation.

DV: Life Expectancy	(1)	(2)	(3)	(4)
Elite Numeracy	0.46***	0.27***	0.28***	0.22**
	(0.10)	(0.09)	(0.10)	(0.11)
GNIpc (log)		2.92***	3.14***	2.77***
		(0.24)	(0.26)	(0.31)
Malaria prevalence		-0.04***	-0.04***	-0.05***
		(0.01)	(0.01)	(0.01)
Existence of OIL in region		1.34***	1.36***	1.20***
		(0.29)	(0.28)	(0.29)
Pre-colonial route			-0.51**	-0.43**
			(0.20)	(0.21)
Colonial railway			0.22	0.19
			(0.26)	(0.26)
Population 1600s (log)			-0.21***	-0.22***
			(0.07)	(0.07)
Slavery Indigenous			0.52	0.32
			(0.32)	(0.33)
Latitude				0.11***
				(0.04)
Distance to the coast				-0.00***
				(0.00)
City Now				0.47*
				(0.26)
Observations	1,183	1,146	1,142	1,118
Adjusted R-squared	0.59	0.67	0.68	0.68
Time FE	Y	Y	Y	Y
Region FE	Y	Y	Y	Y

Notes: These regressions estimate the relationship between elite numeracy and life expectancy for regions with at least 10 rulers. Robust standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively.

Table B.2 shows the effect of elite numeracy on malaria prevalence today. The results show a significant negative relationship between historical elite numeracy and contemporary malaria prevalence. When controlling for country and century fixed effects (column 1), we observe that regions with higher historical elite numeracy experience lower malaria rates today, with a coefficient of 1.70. While the coefficient magnitude decreases when we incorporate contemporary factors (column 2) and historical controls (column 3), it remains statistically significant across all models. When geographical variables (column 4) are included, the magnitude of the coefficient increases. Factors such as the presence of colonial railways, a contemporary city, and a colonial railway show no significant association with current malaria prevalence. We include historical malaria prevalence data from the early

20th century (1900-1964) as an alternative dependent variable. Malaria has been one of the most persistent and debilitating diseases in Sub-Saharan Africa, shaping both demographic and developmental paths over time (Gallup & Sachs, 2001). Including historical prevalence allows us to assess whether the formation of elite numeracy may have influenced the health environment during the early 20th century. We confirm the negative effect of elite numeracy (column 5).

Table B.2: Effect of Elite Numeracy on Malaria Prevalence (2010-2020) using OLS estimation.

Variables	(1)	(2)	(3)	(4)	(5)
		DV: Malaria Prevalence			DV: Historical malaria prevalence
Elite Numeracy	-1.70***	-1.34***	-1.48***	-1.74***	-0.01***
	(0.31)	(0.31)	(0.30)	(0.28)	(0.00)
GNIpc (log)		-10.20***	-9.97***	-9.09***	-0.12***
		(1.10)	(1.15)	(1.12)	(0.02)
Average years of schooling		0.32	0.20	0.62**	0.02***
		(0.27)	(0.27)	(0.26)	(0.00)
Population (2000-2019) (log)		0.30	0.05	-0.12	0.00
		(0.22)	(0.22)	(0.21)	(0.00)
Colonial railway			-0.26	-0.17	0.02**
			(0.80)	(0.78)	(0.01)
Slavery Indigenous			2.92***	1.84**	-0.01
			(1.00)	(0.93)	(0.02)
Precolonial route			0.62	0.84	-0.02**
			(0.59)	(0.56)	(0.01)
Population density 1920 (log)			0.75***	0.78***	0.01***
			(0.20)	(0.18)	(0.00)
Latitude				0.39***	-0.00
				(0.11)	(0.00)
Distance to the coast				0.00*	0.00*
				(0.00)	(0.00)
City Now				-0.30	-0.04***
				(0.93)	(0.01)
Malaria Ecology Index				0.50***	0.01***
				(0.04)	(0.00)
Observations	1,184	1,114	1,114	1,108	981
Adjusted R-squared	0.72	0.76	0.76	0.79	0.79
Time FE	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y

Notes: These regressions estimate the relationship between elite numeracy and life expectancy for regions with at least 10 rulers. Robust standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively.

B.3.2 Instrumental Variable Regression

We incorporate distance measures for four African centres, kingdoms, or regions that possessed writing systems, established trade networks, and administrative structures:

Timbuktu, Mutapa, Ethiopia and Gao. These were associated with early writing systems, the transmission of literacy, and elite formation. Unlike situations where literacy diffused from colonial or recent external sources, these places represent an indigenous African development that could influence neighbouring societies through organic cultural and commercial networks over extended periods. Timbuktu had a reputation as a centre of scholarship, long-distance trade activities, and complex state administration well beyond the African shores (Hunwick, 1999; Hunwick et al., 2008; Jeppie & Diagne, 2008).

Ethiopia developed one of Africa's earliest indigenous writing systems, with the Ge'ez script potentially dating back to around 1300 BCE and being in continuous use for over 3000 years (Negash, 2017). The kingdoms of Mutapa, for example, Monomotapa, developed administrative systems that included systematic record-keeping and quantitative management of tribute, trade, and territorial administration (Duignan & Gann, 1969). Gao, the capital of the Songhai Empire, was another major centre where Islamic learning intersected with extensive trans-Saharan commercial networks (Hunwick, 1999). These centres of early writing technology were by far the most prominent, although regions close to them also used writing technologies extensively (Baten and Alexopolou, 2022). We also utilise the distance to Southern Africa, as our descriptive statistics indicate that the region had higher levels of elite numeracy across all the centuries.

Principal component analysis (PCA) technique was used to derive a composite index of geographic accessibility to these early elite numeracy centres. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was used before applying PCA to test the suitability of the data. The overall KMO value was 0.60, above the 0.5 threshold required for PCA. The KMO value for each distance exceeded the 0.5 threshold, except for Ethiopia, which had a lower value of 0.35. PCA produced one component with an eigenvalue (3.83) significantly higher than those of the other components and accounting for 76.65 per cent of the total variance. It was retained for use as an instrumental variable. This component showed a mix of positive and negative values, which indicated that it captures a meaningful pattern in the geographical distances. The distances to Mutapa, Ethiopia, and to Southern Africa have positive loadings, suggesting that these eastern and southern locations cluster together. In contrast, negative loadings for distances to Timbuktu and Gao indicate that these western locations form a separate grouping. Therefore, this component effectively captures the primary geographical orientation of regions based on variation in the distance measurements.

The p-values for the Durbin score and the Wu-Hausman test are significant, indicating that using IV regression is sensible. Our IV results in Table B.3 show a negative relationship between distance to historical centres and elite numeracy. Our first-stage regression confirms this relationship (F-statistic = 21.06, p =0.000 for life expectancy) and (F-statistic = 11.92, p = 0.000 for malaria prevalence), well above the conventional threshold for weak instruments (Staiger & Stock, 1997). The coefficient is positive and highly significant for life expectancy and negative and highly significant for malaria prevalence. The coefficients of elite numeracy for both are even larger in the IV regression. This may be related to the fact that measurement error might have existed in the OLS regression (Wooldridge, 2010). These estimations are robust and significant, supporting the long-term effect of elite numeracy on health outcomes.

The exclusion restriction for our instrumental variable requires that geographic distance to the five historical centres of writing technology affects present-day health outcomes only through its historical impact on elite numeracy, and not via other factors such as higher income in these centres. We carefully consider potential violations of this assumption. A potential violation might be the spread of specific agricultural practices that could have independently improved health outcomes. To address this potential concern, we control for historical crop density (measured as crop per capita) in the 17th century to proxy increased agricultural practices. Higher crop density could have directly affected health outcomes rather than through elite numeracy. Table B.4 shows that our instrument effectively isolates exogenous variation in the endogenous variable, as evidenced by the inclusion of crop per capita, and that the effect of the instrumented elite numeracy is not removed. In nearly no scholarly study using IV regressions can all potential doubts about fulfilling the exclusion restriction be avoided; hence, we remain cautious, as crop per capita estimates may not fully capture all dimensions of initial development levels.

Table B.3: Instrumental Variable Regressions

Variables	Life Expectancy		Malaria Prevalence	
	First-Stage	2SLS	First-Stage	2SLS
Elite Numeracy		2.68***		-11.60***
		(0.99)		(2.79)
GNIpc (log)	-0.12	3.16***	0.04	-8.68***
	(0.08)	(0.40)	(0.11)	(1.58)
Malaria prevalence	-0.01***	-0.04***		
	(0.00)	(0.02)		
Average years of schooling			-0.03	0.42
			(0.02)	(0.35)
Existence of OIL in region	-0.19***	1.63***		
	(0.07)	(0.37)		
Colonial railway	0.18***	-0.17	0.21***	1.61
	(0.06)	(0.33)	(0.07)	(1.10)
Precolonial route	-0.05	-0.46*	-0.07	-0.86
	(0.06)	(0.27)	(0.06)	(0.89)
Population 1600s (log)	0.08***	-0.42***		
	(0.02)	(0.12)		
Slavery Indigenous	0.04	-0.18	0.06	1.39
	(0.09)	(0.40)	(0.09)	(1.28)
Population density 1920 (log)			0.07***	1.38***
			(0.02)	(0.37)
Latitude	0.08***	-0.02	0.08***	0.73***
	(0.01)	(0.06)	(0.01)	(0.19)
Distance to the coast	-0.01**	-0.00	-0.00	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
City Now	0.22***	-0.23	0.29***	1.95
	(0.08)	(0.42)	(0.09)	(1.50)
Malaria Ecology Index			0.01	0.47***
			(0.00)	(0.06)
Population (2000-2019) (log)			0.01	-0.19
			(0.02)	(0.35)
Historical Centre Proximity	-0.60***		-0.67***	
	(0.13)		(0.13)	
Observations	1,003	1,003	1,032	1,032
R-squared	0.46	0.57	0.45	0.60
Century FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
First-stage F	21.06***		11.92***	
Durbin (score) p-value	0.004		0.204	
Wu-Hausman p-value	0.005		0.216	

Notes: Robust standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively. First-stage regressions show the effect of instruments on Elite Numeracy. 2SLS estimates use historical centre proximity (PCA-based) as an instrument for elite numeracy.

Table B.4: Exclusion Restriction of the Instrumental Variable using Crop per Percapita in the 17th Century.

Variables	Life Expectancy		Malaria Prevalence	
	First-Stage	2SLS	First-Stage	2SLS
Elite Numeracy		2.84***		-12.28***
		(1.07)		(2.94)
GNIpc (log)	-0.13	3.19***	0.04	-8.73***
	(0.08)	(0.42)	(0.11)	(1.63)
Average years of schooling			-0.03	0.41
			(0.02)	(0.36)
Population (2000-2019) (log)			0.01	-0.17
			(0.02)	(0.36)
Colonial railway	0.18***	-0.19	0.21***	1.71
	(0.07)	(0.34)	(0.07)	(1.13)
Slavery Indigenous	0.03	-0.17	0.06	1.36
	(0.09)	(0.41)	(0.09)	(1.31)
Precolonial route	-0.05	0.45	-0.07	-0.90
	(0.06)	(0.28)	(0.06)	(0.92)
Population density 1920 (log)			0.07***	1.48***
			(0.02)	(0.39)
Latitude	0.08***	-0.03	0.08***	0.78***
	(0.01)	(0.07)	(0.01)	(0.20)
Distance to the Coast (km)	-0.00**	-0.00	-0.00	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
City Now	0.22***	-0.26	0.29***	2.09
	(0.08)	(0.44)	(0.09)	(1.55)
Malaria Ecology Index			0.01	0.47***
			(0.01)	(0.06)
Crop Area percapita 17th Century	0.04	-0.17	0.01	0.75
	(0.04)	(0.20)	(0.04)	(0.59)
Average prevalence (2010 to 2020)	-0.01***	-0.04**		
	(0.00)	(0.02)		
Existence of OIL in region	-0.21***	1.73***		
	(0.07)	(0.41)		
Log population density 1600s	0.07***	-0.45***		
	(0.02)	(0.13)		
Historical Centre Proximity	-0.57***		-0.67***	
	(0.13)		(0.13)	
Observations	1,033	1,033	1,032	1,032
Adjusted R-squared	0.46	0.57	0.45	0.59
Time FE	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
First-stage F	18.51***		25.44***	
Durbin (score) p-value	0.004		0.000	
Wu-Hausman p-value	0.005		0.000	

Notes: Robust standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively. The instrument is Proximity to Historical Centres (PCA-based).

B.3.3 The Effect of Mission Shocks

We study the effect of mission presence on health outcomes today to understand if it can serve as a mechanism in this relationship. We are curious whether mission presence leads to insignificant coefficients for elite numeracy. Hypothetically, the presence of Christian missions could have acted as a historical shock, influencing the long-term relationship between elite numeracy and health outcomes. Christian missionary activity in Africa has a long and varied history, with significant expansion occurring during the 19th century. Major Protestant missionary societies established stations across the continent from the 1830s onward (Etherington, 2019). The presence of missions coincided with the beginning of colonial administrative structures and preceded modern health interventions.

Our results in Table B.5 suggest that elite numeracy consistently influences health outcomes, even after controlling for mission presence, though the mission effects vary by outcome. Mission presence is significantly associated with increased life expectancy. Its association with malaria prevalence is negative but not statistically significant. By contrast, a higher number of missions is associated with higher malaria prevalence, consistent with their strategic placement in areas with greater disease burden (Wall, 2015). The number of missions shows no association with life expectancy.

Table B.5: The Effect of Mission Presence on Health Outcomes Today

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Life Expectancy			Malaria Prevalence		
Elite Numeracy	0.21**	0.22**	0.22**	-1.74***	-1.77***	-1.61***
	(0.11)	(0.11)	(0.11)	(0.28)	(0.28)	(0.30)
Mission Presence	0.56**			-0.66		
	(0.23)			(0.63)		
Number of missions up to 1929		0.00			0.03**	
		(0.01)			(0.02)	
Missions per capita			-0.00			0.05***
			(0.01)			(0.02)
GNIpc (log)	2.71***	2.79***	2.79***	-9.11***	-8.91***	-9.13***
	(0.31)	(0.32)	(0.32)	(1.12)	(1.13)	(1.11)
Malaria prevalence	-0.05***	-0.05***	-0.05***			
	(0.01)	(0.01)	(0.01)			
Existence of OIL in region	1.21***	1.20***	1.20***			
	(0.29)	(0.29)	(0.29)			
Precolonial route	-0.43**	-0.42**	-0.43**	0.83	0.96*	0.49
	(0.21)	(0.21)	(0.21)	(0.56)	(0.57)	(0.55)
Colonial railway	0.15	0.18	0.20	-0.15	-0.26	-0.33
	(0.26)	(0.26)	(0.26)	(0.78)	(0.78)	(0.78)
Population 1600s (log)	-0.22***	-0.21***	-0.23***			
	(0.07)	(0.07)	(0.08)			
Slavery Indigenous	0.23	0.31	0.32	1.91**	1.76*	1.82*
	(0.33)	(0.33)	(0.33)	(0.93)	(0.94)	(0.93)
Latitude	0.13***	0.11***	0.11***	0.37***	0.41***	0.43***
	(0.04)	(0.04)	(0.04)	(0.11)	(0.11)	(0.11)
Distance to the Coast (km)	-0.00***	-0.00***	-0.00***	0.00*	0.00**	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
City Now	0.45*	0.45*	0.46*	-0.29	-0.47	0.58
	(0.26)	(0.27)	(0.26)	(0.93)	(0.94)	(0.93)
Years of schooling (2000 to 2019)				0.64**	0.62**	0.69***
				(0.26)	(0.26)	(0.26)
Population (2000-2015) (log)				-0.08	-0.15	0.03
				(0.21)	(0.22)	(0.22)
Population density 1920 (log)				0.78***	0.84***	
				(0.18)	(0.18)	
Malaria Ecology Index				0.50***	0.51***	0.50***
				(0.04)	(0.04)	(0.04)
Observations	1,118	1,118	1,118	1,108	1,108	1,108
Adjusted R-squared	0.68	0.68	0.68	0.79	0.79	0.79
Time FE	Y	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y	Y

Notes: Robust standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively.

B.3.4 Robustness Checks

We conducted several robustness checks to assess the validity and strength of our results. First, because Southern Africa had the highest average levels of elite numeracy across the three centuries, we check for robustness to its exclusion from the model. Its inclusion or exclusion did not alter the findings (column 4 of Tables B.6 and B.7). Secondly, we assess whether elite numeracy had the strongest association during the 17th, 18th or 19th century. We find that both the 17th and 18th centuries had substantial effects on both health outcomes and the 19th-century elite numeracy only for Malaria prevalence (columns 1, 2 and 3 of Tables B.6 and B.7). Thirdly, we included the current level of numeracy as a control variable to examine whether the relationship between elite numeracy and current health outcomes persists even after accounting for contemporary numeracy levels. Numeracy was assessed using the age-heaping methodology based on the ABCC index, a technique developed by A'Hearn et al. (2009) to measure basic numerical skills in populations. Numeracy levels were assessed for individuals born in the decades of the 1950s to 1990s (Ferber & Baten, 2025). The effects of whole-population numeracy on malaria prevalence were insignificant, but it had a positive, significant effect on life expectancy. Nevertheless, these results did not invalidate the influence of early elite numeracy (column 5 of Tables B.6 and B.7).

Moreover, we also assess whether controlling for historical differences in health might alter the significance of elite numeracy (appendix, section B.6.12). For this purpose, we include height differences as a proxy for health. Martin & Baten (2022) report a close correlation between height and population health across long periods. We observe that the elite numeracy coefficients remain significant after adding this control. In addition, while our primary focus is on health outcomes, we examine whether our findings extend to other development outcomes as well. We replicate our main analysis using economic and educational outcomes as dependent variables (appendix, section B.6.11). We consider three categories of alternative outcomes: the Human Development Index (HDI), economic development, and educational development. For economic development, we use Gross

National Income (GNI) per capita, and for educational development, we employ the average years of schooling, finding that elite numeracy also had a positive effect on these variables.

Table B.6: Robustness Checks: Life Expectancy

DV: Life Expectancy	(1) 17th Century	(2) 18th Century	(3) 19th Century	(4) No Southern Africa	(5) Contemporary numeracy
Elite Numeracy	0.71***	0.37*	0.01	0.26**	0.24**
	(0.27)	(0.22)	(0.17)	(0.12)	(0.11)
GNIpc (log)	3.02***	2.73***	2.73***	2.72***	2.98***
	(0.60)	(0.56)	(0.56)	(0.38)	(0.30)
Malaria prevalence	-0.04**	-0.04***	-0.05***	-0.05***	-0.05***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Existence of OIL in region	1.26**	1.13**	1.12**	1.23***	0.97***
	(0.55)	(0.52)	(0.52)	(0.29)	(0.30)
Precolonial route	-0.55	-0.35	-0.49	-0.65***	-0.30
	(0.41)	(0.37)	(0.36)	(0.23)	(0.20)
Colonial railway	0.16	0.11	0.23	0.14	0.01
	(0.48)	(0.47)	(0.46)	(0.29)	(0.26)
Population 1600s (log)	-0.20	-0.22*	-0.23*	-0.29***	-0.33***
	(0.14)	(0.12)	(0.13)	(0.08)	(0.08)
Slavery Indigenous	0.08	0.53	-0.07	0.49	0.24
	(0.66)	(0.50)	(0.66)	(0.38)	(0.32)
Latitude	0.12*	0.08	0.14**	0.12***	0.13***
	(0.07)	(0.06)	(0.06)	(0.04)	(0.03)
Distance to the coast	-0.00*	-0.00**	-0.00**	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
City Now	0.30	0.51	0.42	0.70**	0.42
	(0.50)	(0.46)	(0.46)	(0.30)	(0.27)
Numeracy					0.03***
					(0.01)
Observations	343	382	393	1,038	1,019
Adjusted R-squared	0.64	0.67	0.64	0.68	0.70
Time FE	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y

Notes: Robust standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively.

Table B.7: Robustness Checks: Malaria Prevalence

DV: Malaria Prevalence	(1) 17th Century	(2) 18th Century	(3) 19th Century	(4) No Southern Africa	(5) Contemporary numeracy
Elite Numeracy	-2.22***	-2.92***	-1.38***	-1.48***	-1.69***
	(0.72)	(0.54)	(0.40)	(0.29)	(0.29)
GNIpc (log)	-8.58***	-9.84***	-8.99***	-12.29***	-9.01***
	(2.05)	(2.03)	(2.04)	(1.25)	(1.24)
Average years of schooling	0.57	0.88*	0.46	0.95***	0.60**
	(0.45)	(0.46)	(0.47)	(0.27)	(0.29)
Population (2000-2019) (log)	0.12	-0.17	-0.28	-0.05	0.00
	(0.39)	(0.40)	(0.37)	(0.22)	(0.24)
Colonial railway	-0.60	-0.01	0.29	-0.17	-0.15
	(1.49)	(1.37)	(1.39)	(0.85)	(0.83)
Slavery Indigenous	2.22	2.92*	0.54	3.31***	2.16*
	(1.72)	(1.77)	(1.75)	(1.01)	(1.11)
Precolonial route	1.25	0.76	0.33	0.09	0.92
	(1.03)	(0.98)	(1.02)	(0.59)	(0.58)
Population density 1920 (log)	0.55	0.75**	0.98***	1.16***	0.75***
	(0.34)	(0.32)	(0.33)	(0.19)	(0.19)
Latitude	0.39*	0.53***	0.28	0.59***	0.39***
	(0.22)	(0.19)	(0.19)	(0.11)	(0.11)
Distance to the coast	0.00	0.00	0.00	0.00**	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
City Now	-0.96	0.34	-0.08	-0.10	-0.35
	(1.72)	(1.72)	(1.62)	(0.99)	(1.02)
Malaria Ecology Index	0.49***	0.52***	0.48***	0.52***	0.51***
	(0.07)	(0.07)	(0.07)	(0.04)	(0.04)
Numeracy					-0.03
					(0.02)
Observations	340	377	391	1,034	1,018
Adjusted R-squared	0.77	0.77	0.77	0.77	0.78
Time FE	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y

Notes: Robust standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively.

B.4 Conclusion

We traced regional differences in elite numeracy across the 17th, 18th and 19th centuries. We find that regions with higher elite numeracy in the 17th, 18th, and 19th centuries have better health outcomes today. This relationship persists when controlling for other historical and contemporary factors, indicating that early human capital formation creates path dependencies in health development. Although today's decisions undoubtedly drive a significant portion of current outcomes, the enduring influence of historical numeracy demonstrates that early investments in human capital generate long-term developmental advantages. Therefore, numeracy is relevant not only in contemporary development but also in shaping the long-term health and well-being of populations.

B.5 References

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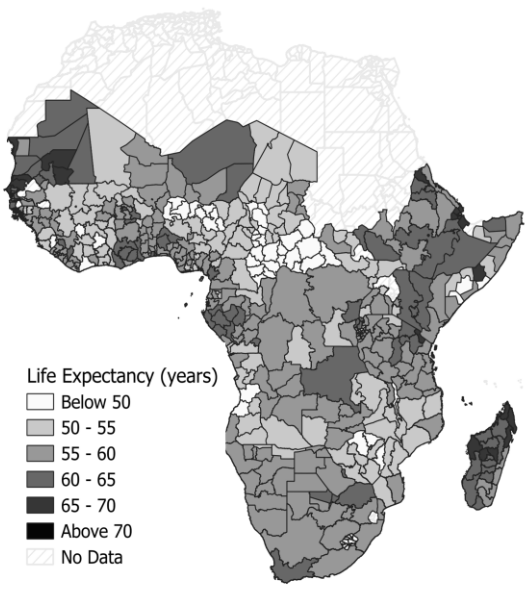
B.6 Appendix

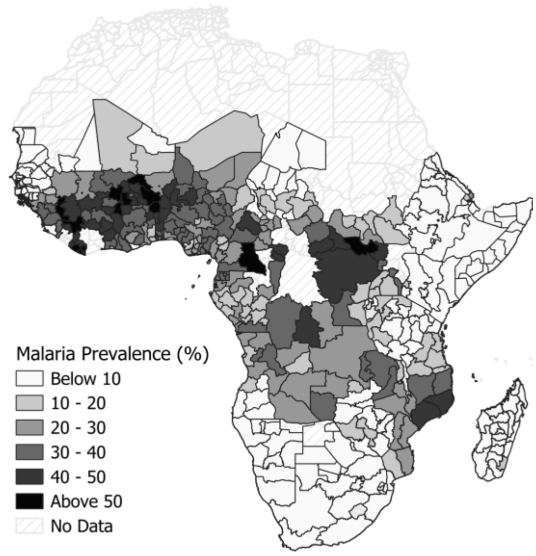
B.6.1 Figures

Figure B.1: Distribution of Life Expectancy by Region in Sub-Saharan Africa 2000-2019



Source: Subnational HDI Database of the Global Data Lab (Smits & Permanyer, 2019)

Figure B.2: Distribution of Malaria Prevalence by Region in Sub-Saharan Africa 2010-2020



Source: Malaria Atlas project database

Figure B.3: 19th Century Elite Numeracy

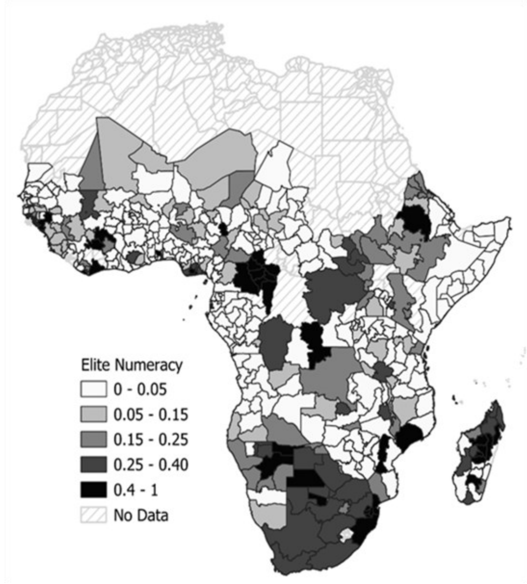


Figure B.4: 18th Century Elite Numeracy

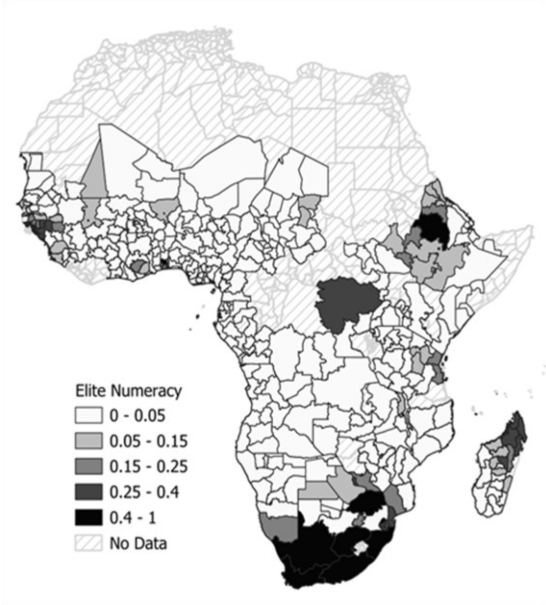
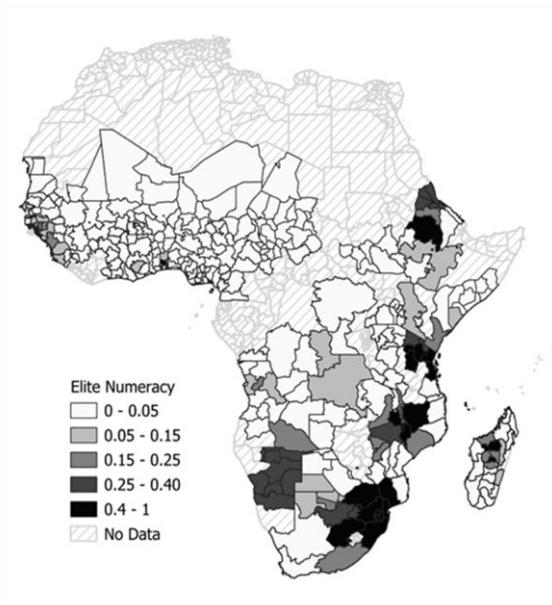


Figure B.5: 17th Century Elite Numeracy



B.6.2 Summary Statistics

Table B.8: Summary Statistics

Variables	Obs	Mean	Median	Std. Dev.	min	max
Life Expectancy (2000-2019)	1183	56.95	56.80	4.42	46.95	69.93
Malaria Prevalence (2010-2020) per 100 Children	1184	18.21	15.22	14.82	0	59.2
Elite Numeracy	1241	0.07	0.03	0.1	0	0.92
Precolonial Route	1213	0.43	0.00	0.5	0	1
Colonial Railway	1213	0.18	0.00	0.38	0	1
Population 1600s (log)	1211	1.2	1.16	1.83	-5.84	6.51
Slavery Indigenous	1209	0.82	1.00	0.38	0	1
Latitude	1241	0.61	5.20	12.74	-33.06	20.53
Distance to Coast (Km)	1199	512.39	408.89	460.33	0.12	3046.41
Gross National Income percapita (log)	1183	7.79	7.53	0.78	6.43	10.71
Oil Presence in Region	1201	0.11	0.00	0.31	0	1
Historical Prevalence of Malaria (1900-1964)	1057	41.05	43.12	18.38	4.83	84.41
City existence now	1185	0.13	0.00	0.34	0	1
Malaria Ecology Index	1241	13.44	12.67	9.26	0	34.31
Average years of schooling (2000-2019)	1183	4.24	4.25	2.52	0	12.05
Number of Missions	1213	4.36	1.00	11.57	0	156
Population (2000-2019) (log)	1169	12.52	12.48	1.66	8.12	16.37

B.6.3 Sources of Data

Table B.9: Sources of Data

Variable	Source	Comments	Access
Malaria Ecology Index	Kiszewski et al (2004	Mean value per admin I. Index computed at a 0.5-degree grid	Kiszewski, A., Mellinger, A., Spielman, A., Malaney, P., Sachs, S. E., & Sachs, J. (2004). A global index representing the stability of malaria transmission. *The American journal of tropical medicine and hygiene*, *70*(5), 486-498.
Historical Prevalence of Malaria (1900-1964)	Snow et al. (2017).	Prevalence in percentage of malaria	Snow, R. W., Sartorius, B., Kyalo, D., Maina, J., Amratia, P., Mundia, C. W., Bejon, P. & Noor, A. M. (2017). The prevalence of Plasmodium falciparum in sub-Saharan Africa since 1900. *Nature*, *550*(7677), 515-518.
Malaria Prevalence	Malaria Atlas project	Proportion of children aged 2 to 10 years with malaria	Malaria Atlas project
Slavery Indigenous	Nunn and Wantchekon (2011)	Slavery: Indicator variable that equals one if there was indigenous slavery in the region	Nunn, N., & Wantchekon, L. (2011). The slave trade and the origins of mistrust in Africa. *American Economic Review*, *101*(7), 3221-3252. https://scholar.harvard.edu/nunn/pages/data-0
Precolonial Explorer routes	Nunn and Wantchekon (2011)	dummy if pre-colonial explorer route in the admin I area	Nunn, N., & Wantchekon, L. (2011). The slave trade and the origins of mistrust in Africa. *American Economic Review*, *101*(7), 3221-3252. https://scholar.harvard.edu/nunn/pages/data-0
Colonial railway	Nunn and Wantchekon (2011) Rueda and Cage (2016)	dummy if colonial railway in the admin I area	Nunn, N., & Wantchekon, L. (2011). The slave trade and the origins of mistrust in Africa. *American Economic Review*, *101*(7), 3221-

			3252. https://scholar.harvard.edu/nunn/pages/data-0 Cagé, J., & Rueda, V. (2016). The Long-Term Impact of the Printing Press in Sub-Saharan Africa. *American Economic Journal: Applied Economics. 8(3)*: 69–99. *http://dx.doi.org/10.1257/app.20140379*
Distance to the Coast (100km)		Distance from centroid of admin I to coast	
Latitude		Absolute latitude measured at the centroid of each admin I.	
Oil Presence	The petroleum dataset: Peace Research Institute Oslo (PRIO)	Petroleum: Indicator variable that equals one if there is an oil field in or overlapping the region	http://www.prio.no/CSCW/Datasets/Geographical-and-Resource/Petroleum-Dataset/Petroleum-Dataset-v11/
City Now existence	Africapolis database	Whether the region has a city now	OECD/SWAC (2020), Africapolis (database), www.africapolis.org (accessed 2024-08-05)
Population density 1920s	Hyde (History database of the Global Environment)	The population density in the administrative region in the 1920s.	Klein Goldewijk, K., A. Beusen, J. Doelman, & E. Stehfest (2017). Anthropogenic land use estimates for the Holocene; HYDE 3.2, Earth System Science Data, 9, 927-953
Population density 1600s	Hyde (History database of the Global Environment)	The population density in the administrative region in the 1600s.	Klein Goldewijk K, Beusen A, Janssen P (2010) Long term dynamic modeling of global population and built-up area in a spatially explicit way: HYDE 3.1. The Holocene 20:565-573.
Gross National Income	(Smits & Permanyer, 2019)	Log Gross National Income per capita in thousands of US Dollars (2011 PPP).	The Subnational HDI Database of the Global Data Lab (Smits & Permanyer, 2019)
Number of Christian Missions	https://www.beckerbastian.net/data	Number of catholic (1929) and protestant missions (up to 1925)	Becker, B & Dulay, D (n.d). Between God and Nation: The Colonial Origins of Democracy Support

			in British Africa, *Studies in Comparative International Development.* Becker, B (2022), The Empire Within: Longitudinal Evidence on the Expansion of Christian Missions in Colonial Africa. *Journal of Historical Political Economy, 2*(2), 333--362. Becker, B., and Meier zu Selhausen F. (n.d). Missionary Legacies of Gender Equality: Evidence from Sub-Saharan Africa, *European Review of Economic History.* https://www.beckerbastian.net/data
Life Expectancy	(Smits & Permanyer, 2019)	Life Expectancy at birth (2000-2019)	The Subnational HDI Database of the Global Data Lab (Smits & Permanyer, 2019)
Population	(Smits & Permanyer, 2019)	Population (2000-2019)	The Subnational HDI Database of the Global Data Lab (Smits & Permanyer, 2019)
Average years of schooling	(Smits & Permanyer, 2019)	Average years of schooling (2000-2019)	The Subnational HDI Database of the Global Data Lab (Smits & Permanyer, 2019)
Contemporary numeracy	Ferber, S., & Baten, J. (2025).	Numeracy assessed using the ABCC index.	Ferber, S., & Baten, J. (2025). Age heaping based numeracy estimates in African regions, 1950–1999: New methodological advances and results. *Economic History of Developing Regions*, 1-34. doi.org/10.1080/20780389.2024.2435935

B.6.4 Measurement of Elite Numeracy: Data Sources

Table B.10: Example of the Data on Rulers. Here: The kingdom of Mangbetu (Monbuttu) in Democratic Republic of Congo, 1761-1874

Begin of rule	End of rule	Name	Birth Year	Death Year
1710	1761	Mebula	-	-
1788	1830	Manzika	-	1830
1830	1860	Nabingali	1815	1860
1860	1867	Tuba (Tukuba)	-	1867
1867	1874	Mbunza	1830	1874

Source: Truhart (1984). p. 45.

Reference

Truhart, P. (1984). Regents of nations. Systematic chronology of states and their political representatives on past and present, Africa/ America. K.G.Saur.

B.6.5 European Contact versus African Origin Writing Systems.

European contact might have played a role in developing the corresponding techniques for recording birth years of rulers and in generating interest for numbers and dates in general. There are several compelling explanations for why interactions with Europeans might not have affected our measure of birth years, even in the absence of "true" elite numeracy. We thus assessed European contact more systematically. Therefore, we defined a measure of European contact which is mainly based on historical descriptions like the one by Oliver and Atmore (2001) about European contacts. Early contact occurred through Saharan trade routes during antiquity and the medieval periods, diminishing with Islam's spread in North Africa. Nevertheless, Christian Sudanese principalities and Ethiopian Empires had occasional interactions. Christian kingdoms of Sudan maintained contact with Europeans through Mediterranean and Nile routes. Portuguese explorations from the 15th century onward expanded connections to territories south of Cape Bojador, reaching Arguin, Senegal, Cape Verde, Sierra Leone, Ghana, and the Gulf of Guinea, facilitating trade routes to India.

The kingdom of Ba-Kongo in Congo had early contacts from the 1480s. The Portuguese expansion in the 15th and 16th centuries led to increased contacts. Early Portuguese visits and trade activities occurred along the coast of present-day Republic and Democratic Republic of Congo, driven by copper and slave trade interests. Inland, the Kasanje principality (modern Angola) engaged in slave trade with Portuguese traders. In Angola, the Lundu and Kalonga principalities, alongside groups such as the Ovimbundu and the Kuba kingdom, had early interactions. Southern Africa saw intensified contacts from the 17th century, with the Dutch Cape Colony establishing relations for food production. The Mutapa empire traded with Portuguese and Arab traders in the 16th century. Shona kingdoms and Kiteve in Zimbabwe also had 16th-century contact with the Portuguese. The Kazembe kingdom, between Kongo and Zambia, engaged with the Portuguese in the 18th century. Along the East African coast, the Kilwa sultanate in Tanzania traded with the Portuguese and French for slaves and ivory from the early 16th century. The Tsonga kingdom (Mozambique/South Africa) traded textiles, ivory, and slaves with the Dutch. In Abyssinia (modern Ethiopia), contact with the Portuguese increased in the 16th century, coinciding with a stagnation of elite numeracy.

The question would now be: Was it perhaps only European priests, European traders and missionaries who recorded the ruler's birth years and other events, and in places where they did not appear, were the ruler lists not recorded? Although European priests, missionaries, traders and travellers documented African political events, scholars argue that Africa had its own systems for recording and calculation. Some suggest that writing systems and mathematical-astronomical developments originated in Africa. Writing systems existed around the Sahara, including Egypt, the Sahel zone, Nubia, and Meroe, millennia before the Common Era (CE). The "Old Nubian" script, developed between 800 CE and 1500 CE, was primarily used in the kingdom of Makuria in central Sudan. Ethiopia and later the Timbuktu region adopted writing systems, while other African regions lacked the prerequisites for their adoption. Ge'ez, one of the world's oldest written languages, dates back to 800 BCE. Arabic scripts and their derivatives were used in Eastern Africa, extending to Madagascar. Arabic scripts and their derivatives were used in Eastern Africa even as far south as today's Madagascar (Simon, 2006). In central and southern Africa, writing systems developed later, and specialised priests transmitted knowledge orally. For example, in the Mutapa kingdom, mhondoro priests recorded the names of rulers and their reign stories. Mathematical and astronomical advancements, including writings of early scholars, were preserved in Timbuktu libraries. Traditional games like Gebet'an or "Mancala", dating back to at least 700 BCE in

Ethiopia, also played a role in numerical training, and these games are still in use today (Natsoulas, 1995). In southern Africa, recording systems partly relied on the adoption of the Arabic script, as seen in Sorabe in Malagasy. European trade contact and Christian missionary activity were contributing factors to elite numeracy in some cases, but they did not exclusively determine it. An example is the Empire of Wolof, which traded extensively with Europeans but did not show a high level of elite numeracy despite close contact. Conversely, the Kingdom of Ba-Kongo and the Abyssinian rulers, which had relatively high levels of numeracy, had established strong governments before European contact. These states may have been more receptive to trading and religious interactions with Europeans due to their high elite human capital and state capability. In our regressions, we will include variables such as precolonial trade routes and railways to account for the effect of "European contact."

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Natsoulas, A. (1995). The game of Mancala with reference to commonalities among the peoples of Ethiopia and in comparison to other African peoples: rules and strategies. *Northeast African Studies, 2*(2), 7-24.

Oliver, R. A., & Atmore, A. (2001). *Medieval Africa, 1250-1800.* Cambridge University Press.

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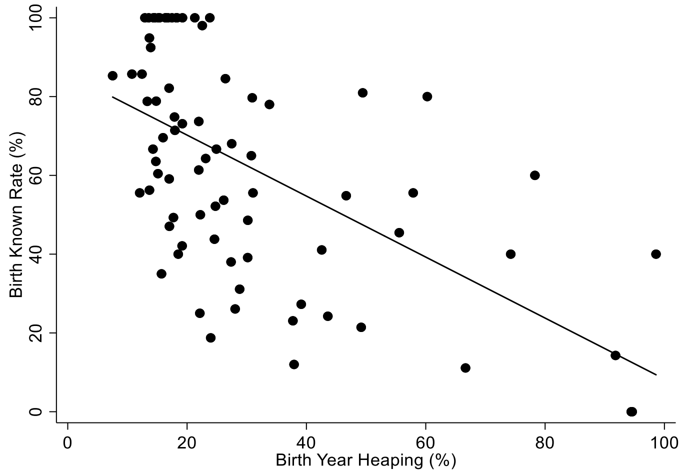
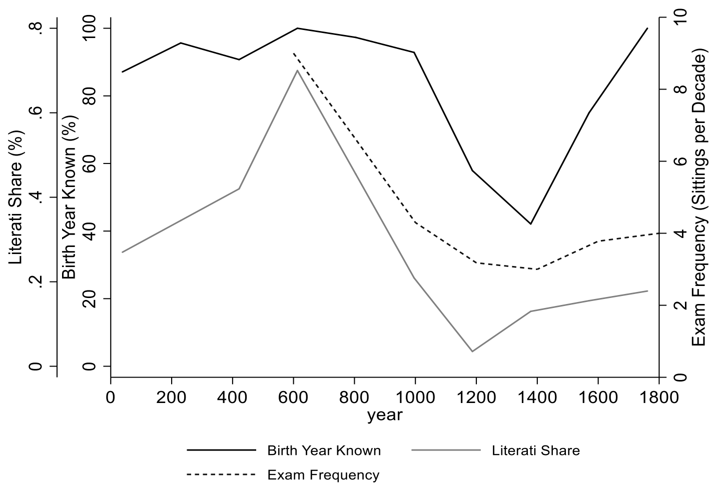
B.6.6 Checking the Ruler-birth-year-known-indicator for Europe, China and Africa

Figure B.6: Birth Year Heaping vs Birth Known Rate (7 European Regions, 800–1800 CE)



Note: Birth year heaping calculated from Cummins' (2017) sample of 115,650 European noblemen (correlation coefficient ρ =-0.58; or ρ =-0.54 where the birth known rate is less than 100%). Source: Cummins (2017), reprocessed in Keywood and Baten (2019)

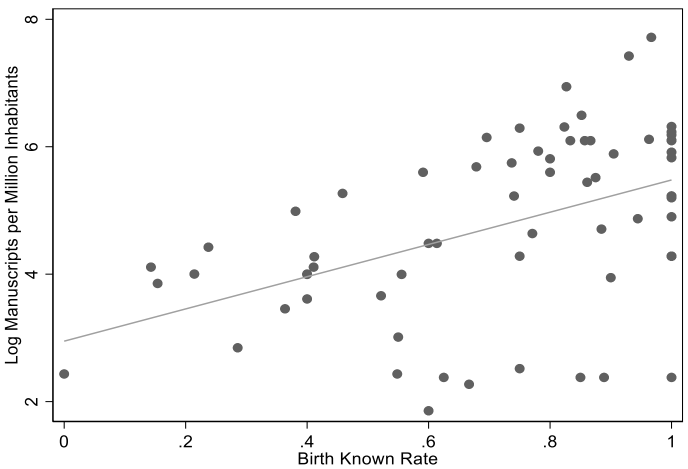
Figure B.7: Elite Numeracy and the "Literati" (China, 0 – 1800 CE)



Note: The "literati system" is the Chinese examination system for elite officials (proxies: exam frequency and literati share of the population, Source: Deng, 1993). The ruler birth year proxy measures elite human capital because the rate of known birth years for rulers is highly correlated with the proxy indicators of elite human capital.

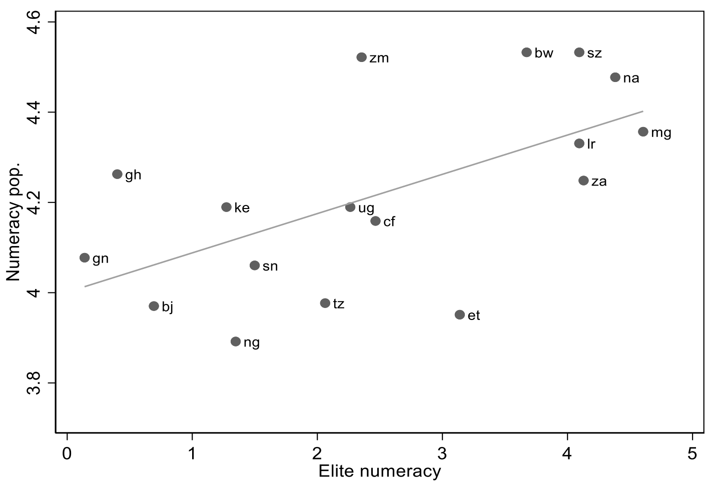
In China, elite numeracy across different centuries has been proposed as a measure. Historically, Chinese elites emerged from rigorous examinations designed to select the most capable candidates, a system known for its difficulty and extensive preparation periods (Deng 1993). Successful candidates, known as "literati", gained esteemed social status and significant income. However, the significance of the literati system varied throughout Chinese history, particularly during periods following nomadic invasions. Keywood and Baten (2021) noted a decline in governing elites' ability to report the birth years of rulers during these periods, suggesting a correlation between societal dynamics and elite numeracy levels.

Figure B.8: Manuscripts vs "Birth Known Rate" (11 European countries, 700-1500 CE)



Note: In this figure, we compare the number of monastery transcripts per million inhabitants (Buringh and Van Zanden 2009) with the share of known rulers' birth years for 11 European countries between 700 and 1500 (Figure modified, using Keywood and Baten (2021)).

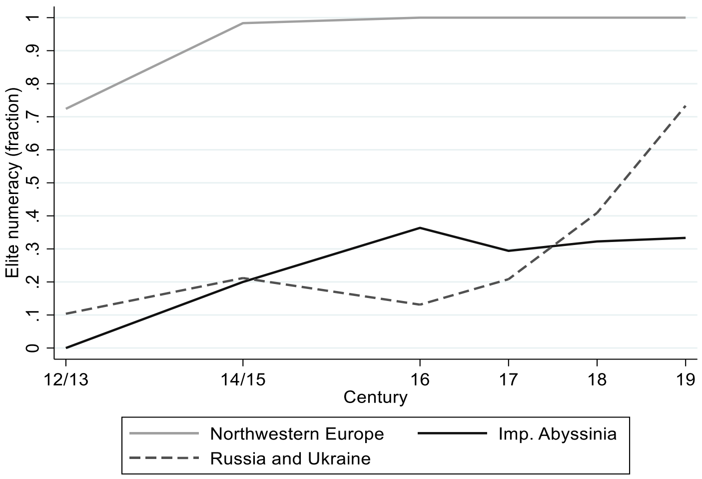
Figure B.9: Comparison of Population and Elite Numeracy in 19th-century Africa



Note: We compare the overall numeracy of the population as estimated by Cappelli and Baten (2021) for the period around 1900 with the elite numeracy estimates for the 19th century, as explained in this paper. The two-letter abbreviations follow the ISO-2 standard, for example, za=South Africa, sd=Sudan, etc. Both population and elite numeracy values are in logs of percent. We included only country-and-century units with at least one birth-year-known case before 1800 to ensure sufficiently high measurement quality.

B.6.7 Potential Biases of the "ruler birth known" Indicator

Figure B.10: Elite Numeracy in Imperial Abyssinia Compared to Selected Eastern and North-western European regions



Note: Russia/Belarus/Ukraine: an average of Russia, Belarus and Ukraine elite numeracy. Source: Data comes from Rogutskaya (2019) and Keywood and Baten (2020). North-western Europe: UK, Netherlands and Belgium. In this figure, we do not claim statistical significance, hence the figure does not include confidence intervals.

Reference

Deng, G. (1993). Development versus stagnation: technological continuity and agricultural progress in pre-modern China. Greenwood Press.

B.6.8 Other Time and Age Recording Systems

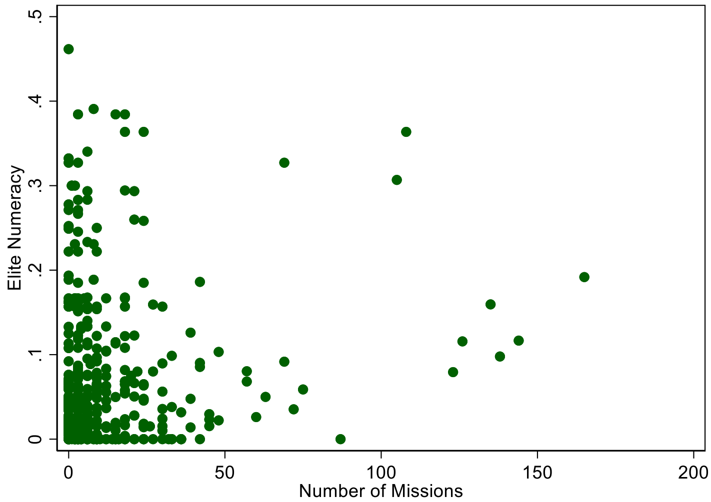
We examined alternative methods for recording age and time in societies other than written records. Some societies used event-based time references, such as "born in the time of war", or "born during a drought", or age-set systems where age was marked by initiation events. Africa exhibited a diverse range of age and time recording practices, none inherently superior to others. However, BA-Kongo and Abyssinia developed more efficient year recording systems compared to others before the 17th century. Despite their initial advantages, conflict, and civil unrest in the 17th to early 19th centuries hindered their economic and social development as they were not benefitting from their initially high elite human capital during the 19th and 20th centuries.

Conversely, regions like Botswana and South Africa boasted high elite numeracy, correlated with overall numeracy in the 18th and 19th centuries. This correlation was evidenced by a positive relationship with population numeracy estimates derived from the age-heaping technique. These countries remain among Africa's wealthiest economies, along with Mauritius, which also demonstrated high numeracy levels. Our indicator, which assesses different age- and time-recording systems, offers insights into long-term development trends. In terms of data sources, some regions had clear documentation practices, such as court records in Congo and Ethiopia or priest caste lineages in Mozambique. In the Sahel region, the Islamic clergy reported ruler lists very often. In areas with oral tradition, quantifiable sources were scarce, necessitating the use of proxy indicators despite potential uncertainties. Our regression analysis focused on high-quality data, excluding regions where the number of rulers was less than ten.

B.6.9 Elite Numeracy and Missionary Activity Relationship.

Following Ricart-Huguet's (2021) framework on elite persistence in colonial contexts, we acknowledge that colonial administrators may have preferentially settled in regions with existing elite populations, subsequently investing more heavily in public health institutions in these areas. There exists a positive but modest association observed in a scatterplot of elite numeracy and number of missions (coefficient = 0.22, statistically significant) at the administrative level one. However, some regions with higher elite numeracy did not receive much missionary activity. In addition, a Mann–Whitney U test indicates significant differences in elite numeracy between regions with and without mission presence, further supporting the hypothesis of unequal exposure to missions. In our study, we control for missionary presence by including variables on mission presence and the number of missions in the study (see Table B.5).

Figure B.11: Scatter plot for Elite Numeracy and Number of Missions



Reference

Ricart-Huguet, J. (2021). Colonial Education, Political Elites, and Regional Political Inequality in Africa. *Comparative Political Studies, 54*(14), 2546–2580.

B.6.10 The Relationship Between Resource Availability and Elite Numeracy

To assess whether elite numeracy primarily reflected administrative culture rather than resource availability, we regressed our elite numeracy measure on key proxies for historical resource availability. Specifically, we used the presence of a city in the 1800s and access to precolonial trade routes. We also included controls for geography: distance to the coast, historical population in the 1600s, and coordinates (longitudes and latitudes) to account for spatial heterogeneity. All proxies for resource availability show no relationship with elite numeracy, and the relationship holds only for geographical factors of latitude and longitude, as seen in Table B.11. The results suggest that there is no systematic evidence that elite numeracy was driven by regional wealth or resource availability.

Table B.11: Resource Availability and Elite Numeracy

DV: Elite Numeracy	Coefficients
Existence of a City in the 1800s	0.01
	(0.17)
Existence of a precolonial route	-0.09
	(0.10)
Distance to the Coast (km)	-0.00
	(0.00)
Log population density 1600s	0.10
	(0.06)
latitude	-1.79***
	(0.18)
Longitude	1.86***
	(0.20)
Observations	1,091
Adjusted R-squared	0.43
Time FE	Y
Country FE	Y

Notes: Robust standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively.

B.6.11 Alternative Development Outcomes Effects

In addition, while our primary focus is on health outcomes, we examine whether our findings extend to other development outcomes. We replicate our main analysis using economic and educational outcomes as dependent variables. We consider three categories of outcomes. For economic development, we use GDP per capita. For educational development, we employ years of schooling and for combined outcomes, the Human Development Index (HDI). Table B.12 shows consistent relationships across the development outcomes. These results suggest that regions with higher elite numeracy levels experience better development outcomes not only in health but also in education and income. This might lead to the question of whether the effects we observe are primarily on income and education, resulting in better health outcomes. However, in our regressions, we control for income and education and find a separate effect of elite numeracy.

Table B.12: Relationship Between Elite Numeracy and Other Development Outcomes

Variable	(1) Human Development Index	(2) GNI percapita (log)	(3) Years of schooling
Elite Numeracy	0.01***	0.02*	0.15**
	(0.00)	(0.01)	(0.07)
Observations	1,159	1,124	1,120
Adjusted R-squared	0.73	0.86	0.71
Time FE	Y	Y	Y
Controls	Y	Y	Y
Region FE	Y	Y	Y

Notes: These regressions show our model, which estimates the relationship between elite numeracy and DVs for regions with at least 10 rulers. Robust standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively. Controls include colonial railway, precolonial route, slavery, distance to the coast, presence of oil in the region, malaria ecology index, population density, distance to the city, and mission presence.

B.6.12 Role of Historical Health Conditions

We examine whether historical health conditions drive contemporary health outcomes. If regions with better historical health both produced higher elite numeracy in the past and maintained better health into the present, then elite numeracy would be epiphenomenal: correlated with but not causally related to contemporary health outcomes. We control for historical health conditions using average adult height in the 1800s, drawn from the Clio Infra database (Baten and Blum, 2012). Height is a measure of population health that reflects childhood nutrition, disease burden, and living conditions during the developmental years. Table B.13 shows that elite numeracy matters independently. For malaria prevalence, historical health conditions show a substantial independent effect, larger than elite numeracy's effect, confirming that better historical health conditions created advantages that persist in shaping contemporary disease patterns. While for life expectancy, elite numeracy matters, historical health does not. Therefore, our results suggest that both historical health conditions and elite numeracy contribute to contemporary health outcomes.

Table B.13: Robustness to Historical Health Conditions

Variables	(1) Life Expectancy	(2) Prevalence
Elite Numeracy	0.59***	-2.57***
	(0.16)	(0.36)
Height 1800s	-0.05	-2.06***
	(0.08)	(0.15)
GNIpc (log)	0.64***	-1.44**
	(0.22)	(0.62)
Years of schooling (2000 to 2019)		-0.43*
		(0.23)
Population (2000-2015) (log)		0.10
		(0.31)
Pre-colonial route	-0.42	3.25***
	(0.32)	(0.88)
Colonial railway	-1.27***	1.30
	(0.44)	(1.11)
Population density 1920 (log)		1.77***
		(0.27)
Slavery Indigenous	1.57***	0.85
	(0.52)	(0.85)
Latitude	0.01	-0.10**
	(0.01)	(0.04)
Distance to the Coast (km)	-0.00***	0.01***
	(0.00)	(0.00)
City Now	1.75***	-2.75**
	(0.45)	(1.12)
Malaria Ecology Index		0.83***
		(0.04)
Malaria prevalence	-0.07***	
	(0.01)	
Existence of OIL in region	-1.31***	
	(0.39)	
Population 1600s (log)	0.03	
	(0.09)	
Observations	921	917
Adjusted R-squared	0.25	0.53
Time FE	Y	Y
Country FE	Y	Y

Notes: Robust standard errors in parentheses, ***, **, * significant at the 1, 5, and 10%-level respectively.

C Health Numeracy, Health Literacy, and Malaria in Gabon: A Validation and Behavioural Analysis[2]

Abstract

Health Numeracy (HN) and Health Literacy (HL) affect individuals' ability to understand and use health information for decision-making. There is limited evidence on validated HN and HL measures in Gabon and their relationship to malaria-related health behaviours. We conducted a cross-sectional household survey across urban and rural areas of Gabon. HL was measured using the French HLS-EU-Q16, and HN was assessed using the Numeracy Understanding in Medicine scale. Both scales were validated using reliability and validity analyses, applying Classical Test Theory (CTT) and Item Response Theory (IRT) prior to subsequent analysis. Malaria health behaviours included the use of bed nets, indoor residual spraying (IRS), treatment-seeking for illness, medication adherence, bush clearing and asking healthcare practitioners questions. Multivariable Logistic regression models examined the association between HN, HL and malaria behaviours, adjusting for demographic, socioeconomic, and health-environmental factors. Mediation analyses examined whether dosage knowledge and asking questions mediated relationships between HL/HN and behaviours. The scales showed strong psychometric properties, supporting their use to assess HL and HN. Overall, 60 per cent of the respondents had sufficient HL, and the average HN score was 6.12 out of 10. Higher scores were observed among participants with at least secondary education and those living in urban areas. HN supported treatment-seeking decisions, while HL was mainly associated with dosing knowledge. Both HL and HN are important for treatment adherence and engagement with healthcare practitioners. Mediation analyses revealed that HL influenced treatment-seeking behaviours entirely indirectly through asking questions. These validated measures provide reliable tools to assess HL and HN in Gabon and illustrate their relevance for malaria prevention and treatment behaviours.

[2] This chapter is based upon joint work with Saidou Mahmoudou and Ynous Djida and Bertrand Lell. I contributed approximately 85 per cent to this research paper.

C.1 Introduction

Malaria remains one of the leading causes of illness and death in sub-Saharan Africa (SSA) (World Health Organization [WHO], 2024). Despite significant efforts to eliminate and control malaria, the disease burden persists, especially where transmission occurs throughout the year. Gabon bears a substantial malaria burden, with the disease ranking among the leading causes of morbidity and mortality, particularly among children under five years of age and pregnant women. The country experiences perennial malaria transmission facilitated by its equatorial climate, which provides optimal breeding conditions for mosquito vectors (Sima-Biyang et al., 2024).

Effective malaria control requires a comprehensive approach combining vector control, prompt diagnosis and treatment, and preventive interventions (WHO, 2015, 2023, 2024). The success of these interventions depends on individual and community behaviours, including consistent use of insecticide-treated bed nets, prompt care-seeking when symptoms arise, adherence to antimalarial treatment regimens, and participation in community-based vector control activities (Chuma et al., 2010; Nonvignon et al., 2016). Central to adopting and maintaining these behaviours is individuals' and communities' ability to understand and act on health information, and to translate it into protective actions. Education, socioeconomic status, language proficiency, cultural beliefs, and access to healthcare shape how people engage with health information. Health literacy and health numeracy are also important, as they form core skills that enable individuals to understand, evaluate, and apply health information effectively.

Health Literacy (HL), defined as the ability to access, understand, appraise, and apply health information (Sørensen et al., 2012), is a key determinant of health behaviours and service utilisation (Aaby et al., 2017; Nutbeam, 2008). It is a multidimensional construct that includes functional literacy (the ability to read and comprehend health materials), communicative literacy (the ability to extract and apply information in changing circumstances), and critical literacy (the ability to critically analyse and use information to exert control over health situations) (Nutbeam, 2000). Health Numeracy (HN), while related to HL, represents a distinct construct defined as the ability to access, process, interpret, and act on numerical health information (Golbeck et al., 2005; Reyna et al., 2009). HN encompasses skills such as understanding risk magnitudes, interpreting medical statistics, calculating medication dosages, and making probabilistic judgments about treatment options (Ancker & Kaufman, 2007; Peters, 2012).

HL and HN are interrelated components of health competence, though they represent conceptually and empirically distinct constructs with unique influences on health behaviours (Osborn et al., 2013; Reyna et al., 2009). HL primarily involves comprehension and communication skills related to verbal and written health information, while HN specifically addresses numerical reasoning and quantitative decision-making (Galesic & Garcia-Retamero, 2011). Studies have shown that individuals may have sufficient general literacy but find it challenging to perform numerical health tasks, and conversely, that numeracy skills can compensate for lower literacy levels in certain situations (Apter et al., 2008; Rothman et al., 2008). Distinguishing between HN and HL is relevant for health behaviours that involve both information comprehension and quantitative reasoning, such as understanding disease risk, calculating appropriate medication doses, or weighing treatment options based on probabilistic outcomes (Reyna & Brainerd, 2007). Therefore, it is important to assess them independently to inform the development of targeted interventions that address their specific roles in health outcomes.

Research has examined the relationship between HL, HN, and various health outcomes, including medication adherence (Houts et al., 2006; Reyna et al., 2009), diabetes control (Cavanaugh et al., 2008; Mostert et al., 2025), smoking (Adewole et al., 2021; Diaz, 2024), COVID-19 responses (Best, 2020; Lau et al., 2022), general health-seeking behaviours (Akakpo & Neuerer, 2024; Bektas et al., 2021; Steinke et al., 2021; Svendsen et al., 2020), non-communicable diseases (Billany et al.,2023; Nutbeam, 2008; Osborne et al., 2022), nutrition (Bíró et al. 2023), vaccination (Barbieri et al., 2025) and cancer screening (Ciampa et al., 2010; Schwartz et al., 1997; Smith et al., 2016). Individuals with higher HL and HN consistently demonstrate healthier lifestyle patterns, fewer risky health behaviours, and better health outcomes. They are better positioned to evaluate risks, understand medication dosages, and engage with health information and health-promoting behaviours (Berkman et al., 2011; Lipkus & Peters, 2009; Peters et al., 2007). People with lower HN skills are more likely to ignore numerical information and instead rely on intuitions based on emotional states and other extraneous factors, such as their trust in, or distrust of, the information source.

The role of HL and HN in malaria control behaviours represents a vital yet understudied area. Malaria control encompasses diverse practices: preventive behaviours such as bed net use and participation in vector control activities require understanding of malaria transmission and consistent application of protective actions; treatment-seeking behaviours require recognition of symptoms, risk assessment, and timely healthcare access; while treatment adherence depends on comprehension of medication instructions, dosage calculations, and sustained behavioural commitment (Heggenhougen et al., 2003; Williams & Jones, 2004). These requirements suggest that HL and HN may differentially influence various aspects of malaria control. While multiple factors, including knowledge, economic factors, demographic factors, perceived susceptibility, and perceived barriers influence malaria control behaviours (Ataka et al., 2011; Chuma et al., 2010; Deressa & Ali, 2009; Dunn et al., 2011), the specific contributions of HL and HN remain poorly characterised.

Emerging evidence suggests HL influences malaria-related behaviours in specific settings. In Ethiopia, malaria HL was identified as both a barrier and facilitator to insecticide-treated bed net utilisation and prompt diagnosis and treatment, with individuals with higher malaria HL demonstrating better adherence to malaria prevention measures (Zerdo et al., 2022). A systematic review of health education interventions across SSA found that health education significantly improved both malaria knowledge and insecticide-treated net usage (Onyinyechi et al., 2023). Studies in Ghana found that HL interventions using co-created educational materials, including interactive board games and brochures, improved caregiver-health provider relationships and enhanced participatory approaches to malaria management among caregivers of children under five (Boateng et al., 2021). Similarly, caregivers with high HL incurred higher household costs for managing malaria in children under five than those with lower HL, possibly reflecting more proactive healthcare-seeking behaviour and use of formal health services (Ofori Boateng et al., 2025). Despite emerging evidence on HL, the contribution of HN to malaria prevention and control has not been investigated. Moreover, barriers to effective malaria management persist across many SSA countries, including misconceptions about disease causation, reliance on traditional healing methods as first-line treatment, and structural barriers such as distance to health facilities and medication costs, which shape how health information is interpreted and acted upon (Falchetta et al., 2020; Maslove et al., 2009; Phok et al., 2022).

Various instruments have been developed to assess HL globally, ranging from functional literacy measures such as the Rapid Estimate of Adult Literacy in Medicine (REALM) (Murphy et al., 1993) and Test of Functional Health Literacy in Adults (TOFHLA) (Parker et al., 1995) to instruments that assess multiple HL dimensions. The European Health Literacy Survey Questionnaire (HLS-EU-Q47) and its shortened version, the HLS-EU-Q16, provide broad and detailed measures of HL, assessing individuals' abilities to access, understand, appraise, and apply health information across healthcare, disease prevention, and health promotion domains (Sørensen et al., 2015). The HLS-EU-Q16 has been adopted to assess HL and examine its relationship with health behaviours across diverse populations (Amanu et al., 2023; Lorini et al., 2019; Sørensen et al., 2024; Storms et al., 2017). Within Africa, applications have been documented in Cameroon (Soh & Wamba, 2022) and Ghana (Boateng et al., 2020). However, no psychometric evaluation of the HLS-EU-Q16 has been conducted in Gabon.

The measurement of HN in African populations is even more limited. Most existing instruments were developed and validated in non-African populations, limiting their applicability in African contexts due to differences in language, educational systems, and cultural perceptions of numbers and health communication. Available HN tools fall into two categories. General instruments include the General Health Numeracy Test (Osborn et al., 2013), Berlin Numeracy Test (Cokely et al., 2012), Newest Vital Sign (Weiss et al., 2005), Lipkus Numeracy Scale (Lipkus et al., 2001), Schwartz Numeracy Scale (Schwartz et al., 1997), and Subjective Numeracy Scale (Fagerlin et al., 2007), which assess probability understanding, percentage calculation, risk interpretation, and self-perceived numerical ability. Furthermore, there are disease-specific instruments, such as the Diabetes Numeracy

Tests (Huizinga et al., 2008; White et al., 2011) and Asthma Numeracy Questionnaire (Apter et al., 2006), that evaluate condition-specific management tasks. The Numeracy Understanding in Medicine Instrument (NUMi), designed to assess basic arithmetic, risk interpretation, and comprehension of quantitative health information (Jacobs et al., 2016; Schapira et al., 2012, 2014), has demonstrated strong psychometric properties in diverse settings (Buljan et al., 2019; Taylor & Byrne-Davis, 2016). Its applicability in African populations has not been examined.

Our study validates tools for assessing HN and HL in Gabon, and then examines their role in malaria control behaviours. The rest of this chapter is organised as follows. Section 2 describes the data sources and explains our methodology for the subsequent analyses. Section 3 validates the HL and HN measures for use in the Gabonese context and establishes their psychometric properties. Section 4 explores the associations between these validated measures and malaria prevention and treatment behaviours, including bed net use, indoor residual spraying, environmental management, treatment-seeking patterns, medication adherence, and patient engagement with healthcare providers. Section 5 discusses the results, and the final section provides the conclusion.

C.2 Data and Methods

C.2.1 Study Design and Setting

We conducted a cross-sectional household survey using quantitative methods from June to July 2025 in selected areas of the Moyen-Ogoueé, Ngounié, and Estuaire provinces of Gabon. Data collection took place in Lambaréné, Fourplace, and Sindara, which represent urban and rural contexts. The study was reviewed by the Institutional Scientific Review Board (SRC) and approved by the Institutional Ethics Committee of the Centre de Recherches Médicales de Lambaréné (CERMEL) (2024-04). The target population of this study consisted of residents of Gabon aged 15 and older.

C.2.2 Sample Size Determination and Allocation

Household enumeration data from SUDESA (the French version of the Health and Demographic Surveillance System (HDSS)) supplemented by aerial map analysis identified about 5,800 households across the three study areas: Lambaréné (about 5,457 households), Fourplace (80 households), and Sindara (263 households) (Centre de Recherches Médicales de Lambaréné [CERMEL], n.d.). The household counts for Fourplace and Sindara were based on complete village registries, while the Lambaréné estimate was derived from SUDESA records and aerial mapping, as no complete household registry was available. To determine the sample size, Cochran's formula (Cochran, 1977) was used, adjusted with the finite population correction (FPC). The formula is given as:

$$n_0 = Z\alpha/_2{}^2 * \frac{pq}{e^2} \tag{2}$$

where n_0 denotes the initial sample size, $Z\alpha/_2$ is the reliability coefficient of standard error at 5% level of significance=1.96, p= proportion estimate of the prevalence of malaria (19%, Direction Générale de la Statistique (DGS) et ICF 2023), and e refers to the level of standard error tolerated/ precision (5%). Therefore, the minimum sample size for the study is 297 households, after adjusting for missing data and non-response by 20 per cent (Althubaiti, 2023; Bujang, 2021).

C.2.3 Household Selection

A multi-stage sampling approach was used to select households. In Fourplace and Sindara, where complete household registries were available from SUDESA, systematic probability sampling was implemented. Households were selected using equal-probability intervals, with the starting point chosen at random. Within each sampled household, available eligible members were invited to participate. In Lambaréné, because no comprehensive sampling frame existed, we implemented stratified quota sampling using the SUDESA building maps from CERMEL as a geographic reference. Lambaréné was subdivided into 13 distinct neighbourhoods (referred to as first districts) named: Abongo, Dakar, Grand Village I, Sainte-Thérèse, Adouma, Château, Grand Village II, Faisceaux, Lalala, Moussamoukougou, Point V, Atongowanga and City Centre. To ensure geographic representation, we allocated neighbourhood-specific target sample sizes (20 to 30 households per neighbourhood) proportional to estimated building densities derived from the aerial mapping. Within each neighbourhood, systematic door-to-door visits along predetermined routes were used to select households to achieve neighbourhood-specific targets. The study protocol allowed recruitment of up to 2 individuals per household with multiple eligible members. However, in practice, most households (approximately 95%) contributed only one participant due to member availability. Only 13 households contributed 2 participants, yielding a sample of 491 unique households. For households with two members, interviews were conducted individually and privately to prevent response bias. The final sample comprised 516 respondents after excluding participants with completely missing data in key sections, distributed as follows: Lambaréné 377 (73.1%), Fourplace 38 (7.4%), Sindara 64 (12.4%), and Medang Nkoghe 37 (7.1%). Medang Nkoghe, an additional rural village in Moyen-Ogooué province, was included during data collection to strengthen rural representation. Observed differences in totals across variables are due to missing data.

C.2.4 Data Collection

Data were collected using a questionnaire on various characteristics, including socio-demographic, economic, health environment, knowledge about malaria, HL, HN, and malaria control behaviours. Questions for HL were adapted from the European Health Literacy Survey Questionnaire, short version comprising 16 items (HLS-EU-Q16 French version) (Rouquette et al., 2018) as developed by the HLS-EU Consortium (Sørensen et al., 2012, 2015). Although the lengthier version of HLS-EU-Q, comprising 47 items of HL skills, may provide optimal validity and reliability, a shorter version enhances the feasibility of measuring HL as part of a large-scale surveillance instrument (Bann et al., 2012).

The French version of HLS-EU-Q16 was translated from the validated English questionnaire HLS-EU-Q16 and tested for psychometric properties to enable its use in surveys of HL for the general adult population (Rouquette et al., 2018). This version also captures aspects of health care, disease prevention, and health promotion, as well as all features related to accessing/obtaining information relevant to health, understanding information relevant to health, processing/appraising information relevant to health, and applying/using information relevant to health. This existing French version facilitates implementation, as French is the official language of Gabon, while maintaining the psychometric integrity of the original instrument. Further, the utility of the HLS for African populations has been demonstrated through its successful cultural adaptation and validation in Ghana, where researchers have developed a culturally adapted version in the Ghanaian language (Akan; Asante Twi) (Boateng et al., 2020) and Cameroon, where it was adapted for both English and French speaking populations (Soh & Wamba, 2022). The version was validated in Gabon, as shown in the results section of this study. The HL scale is in Part I of the questionnaire, Section C.5.2, in the Appendix.

The HN measurement was adapted from an existing instrument, the Numeracy Understanding in Medicine instrument (NUMi), which comprises 20 numerical tasks placed in the health context with multiple-choice answers (Schapira et al., 2012). The instrument measures HN across four domains, each with 5 questions: Number sense, Probability, Statistics, and Tables and Graphs, based on theoretical frameworks and practical insights (Golbeck et al., 2005; Reyna et al., 2009). It was developed using a unidimensional framework. Each question has multiple-choice answers, and the task is to select the correct answer from the options provided. The final score is the sum of correct answers (range 0 to 20). Higher NUMi scores indicate greater health numeracy (Schapira et al., 2012, 2014).

The adaptation process involved following the recommendations of Wild et al. (2005) for the translation and cultural adaptation of measures. The translation of the NUMi scale from English to French was conducted through a group translation process involving five experts in statistics, sociology, psychometrics, general medicine, and public health. The translations were compared by consensus, resulting in a final version understandable to French-speaking individuals. The translation maintained equivalence with the already-validated English items. To improve content validity, the names of the scale's characters were changed to Gabonese or French names, making them more culturally appropriate for the target population. Disease names were modified to reflect common health conditions in Gabon, including malaria, HIV, diabetes, hepatitis, and High Blood Pressure. The original numerical units were retained, except where local measurement systems required adjustments, such as converting from pounds to kilograms or from Fahrenheit to Celsius. The original NUMi development sorted items by difficulty parameters, with selection within each level based on discrimination parameters and content balance (Schapira et al., 2014).

We selected 10 items based on these principles, selecting questions that varied in difficulty and covered different numerical competencies relevant to health decision-making in Gabon. The scale is provided in part G of the questionnaire (Section C.5.2, appendix).

Behaviours in malaria prevention and treatment included bednet use, treatment-seeking, indoor residual spraying, bush clearing and proper treatment uptake. There were seven questions on malaria-related health behaviours. Four of these were assessed on a five-point scale. For "use of bed nets," "seeking care when ill," "taking household members with fever or cough to a doctor," and "completing prescribed medication," responses ranged from "Always" (score 4) to "Never" (score 0). Two questions were assessed with yes/no/not sure responses: "participation in indoor residual spraying," and "clearing bushes around the home". For these, "Yes" was scored 1, "Not sure", and "No" were scored 0. The final question asked about "asking health practitioners questions about malaria or other illnesses," and was also scored on the same five-point scale from "Always" (4) to "Never" (0). A question on knowledge of dosing, "knowledge of correct dosing when prescribed antimalarial treatment", was also included and measured as a binary response (yes and no).

The content and cultural relevance of the questionnaire were assessed before data collection, when a panel of stakeholders, including public health experts, sociologists, and health workers, reviewed all items for clarity, objectivity, and cultural appropriateness. A pilot study was conducted with 20 participants from the target population to evaluate the questionnaire's acceptability and ease of response. Overall, questions were clear and well understood, and no wording adjustments were necessary. The questionnaire details are provided in section C.5.2 in the Appendix.

Individuals who were accessible and willing to participate at the time of data collection were included. When members of a selected household were absent, the nearest neighbouring household was conveniently selected to maintain sample continuity and minimise disruptions to data collection. All participants were provided with written information regarding the study objectives, voluntary participation, and potential risks, and written informed consent was obtained before participation. For individuals under 18 years, prior consent from their parents or legal guardians was obtained. Data collection was conducted by trained interviewers in French, the official language of Gabon, with no personal identifying information recorded and no economic compensation provided for participation. Data were collected using REDCap, which includes built-in range and consistency checks. Data cleaning procedures were applied to identify and correct errors, handle missing values, and resolve logical inconsistencies before analysis.

C.2.5 Analysis

First, descriptive and summary statistics were used to characterise the study variables. Second, the HN and HL scales were analysed for their psychometric properties, using validation methods appropriate to each scale and its response format. Starting with the HL scale, internal consistency was assessed using Cronbach's alpha and McDonald's omega to determine whether the items measured a coherent construct; values of 0.70 or higher were considered satisfactory (Nunnally, 1978). Floor and ceiling effects were evaluated by calculating the percentages of respondents who achieved the minimum possible score (floor effect) and the maximum possible score (ceiling effect). This was done to ensure the scale adequately discriminated among respondents across its full measurement range.

The HL items, originally measured on a 4-point likert scale (very easy, easy, difficult, very difficult), were dichotomised for psychometric analysis. Respondents who answered at least 14 items were included, with any missing responses coded as 0. Participants who answered fewer than 14 items were treated as missing. Overall, the missing response rate was approximately 2.3 per cent (Pelikan & Ganahl, 2017). The "very easy" and "easy" categories were merged into a single category, while the "difficult" and "very difficult" categories were combined into another category. The scale score ranged from 0 to 16. This dichotomisation aligns with standard HLS-EU-Q16 scoring conventions (Rouquette et al., 2018; Sørensen et al., 2015).

The dimensional structure of the scale was examined using exploratory factor analysis with principal component extraction to identify eigenvalues, factor loadings, and the proportion of variance explained by each factor, supported by a scree plot. Suitability for factor analysis was confirmed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity, with KMO above or equal to 0.80 and $p < 0.05$ indicating adequacy.

Loevinger's coefficient of homogeneity was then calculated to assess scalability, with values above 0.30 showing acceptable scale coherence (Mokken, 1971; Sijtsma & van der Ark, 2020). These analyses ensured the scale had sufficient unidimensionality for one-parameter logistic modelling.

Psychometric properties were evaluated using the one-parameter logistic (1PL) item response theory (IRT) model under a marginal maximum likelihood estimation framework (De Ayala, 2009; Embretson & Reise, 2013). The 1PL model, mathematically equivalent to the Rasch model but employing different estimation procedures, assumes that the probability of endorsing an item depends on the difference between a person's latent ability and the item's difficulty parameter, with all items constrained to equal discrimination. Further, to ensure the validity of the IRT model and assess whether the scale supports unidimensionality and the use of total scores, the local independence assumption was evaluated using Yen's Q3 statistic. Following Christensen et al. (2017), absolute Q3 values above 0.30 were interpreted as evidence of substantial local dependence and flagged for further examination. The proportion of item pairs exceeding this threshold was calculated to evaluate the overall extent of local dependence. Proportions below 5 per cent are considered indicative of excellent adherence to the local independence assumption (Chen and Thissen, 1997).

We also assessed known-groups validity by examining whether the HL discriminates between groups expected to differ in HL using both categorical (Chi-square tests) and continuous (Kruskal-Wallis tests) analytical approaches (Kimberlin & Winterstein, 2008; Mokkink et al., 2010). Based on existing literature documenting strong associations between HL and education (Stormacq et al., 2019; Svendsen et al., 2020), and urban-rural residence (Aljassim & Ostini, 2020; Wang et al., 2020), we hypothesised that HL would show significant differences across these characteristics. Conversely, given the inconsistent or minimal gender differences observed in European HL studies (Bergman et al., 2023), we hypothesised that there would be no significant sex differences. Kruskal-Wallis tests were used rather than parametric alternatives because the HL scores were non-normal, as seen in the appendix figure C.2.

Differential Item Functioning (DIF) for the HL scale was assessed across sex, age, and education to ensure measurement invariance using both logistic regression models and the Mantel-Haenszel method. The groupings were based on age (above 45 versus below) and secondary education or higher versus less than secondary education. Items were considered to show meaningful DIF only if both methods detected significant effects ($p < 0.05$), and if differences in item difficulty exceeded 0.25 logit or if more than 25 per cent of items were affected in the same direction. For items meeting these criteria, item difficulties were estimated separately for each group (Rouquette et al., 2016, 2019).

Similarly, the HN scale was analysed. Internal consistency was assessed using the Kuder-Richardson 20 (KR20), appropriate for dichotomous items (correct versus incorrect) (Richardson & Kuder, 1939), with values above 0.70 considered satisfactory. Its validity was assessed using correlations and mean comparisons using Analysis of Variance (ANOVA) to test differences in HN scores across sex, age, education, residence, HL, and employment status. Classical Test Theory (CTT) item statistics were first estimated. Item difficulty was calculated as the proportion of correct responses, with values between 0.20 and 0.80 considered optimal. Item discrimination was assessed using the point-biserial correlation between item responses and total scores, with values above or equal to 0.20 indicating adequate discrimination.

Before fitting IRT models, three assumptions were evaluated: unidimensionality, monotonicity, and local independence (Van Der Linden & Hambleton, 1997). Mokken scale analysis assessed these prerequisites. Unidimensionality was evaluated using Loevinger's coefficient of homogeneity (H), with values above 0.3 considered satisfactory. Monotonicity was assessed to confirm that the probability of a correct response increases with higher latent ability, and items violating this assumption were flagged. Local independence, the assumption that item responses are conditionally independent given the latent trait, was examined using Yen's Q3 statistic as described for the HL scale.

After confirming that the assumptions were met, the IRT model was fitted to estimate item parameters and person abilities, with conclusions drawn from the Test Information Function (TIF) and model fit indices. Log-likelihood ratio tests compared the one-parameter logistic (1PL) model, assuming equal discrimination, with a two-parameter logistic (2PL) model, allowing item discrimination to vary. A three-parameter model including guessing was not estimated because respondents were instructed to leave items blank if unsure of the answer. Estimated parameters included item difficulty (the ability level at which a respondent has a 50% probability of a correct response, ranging from -3.0 to +3.0) and item discrimination (ranging from 0 to 3, indicating the steepness of the item characteristic curve). The TIF was examined to determine the ability range where the scale provides maximum measurement precision.

DIF was assessed to evaluate measurement invariance across subgroups defined by age, sex, education, and health literacy (HL), as these factors may influence understanding or familiarity with items. DIF was tested using both logistic regression and the Mantel-Haenszel method. The groupings were based on age (above 45 versus below), sufficient HL versus inadequate HL, and secondary education or higher versus less than secondary education. Items were flagged for meaningful DIF only if both methods identified statistically significant effects ($p < 0.05$), following recommendations that DIF conclusions should be robust across analytical approaches (Teresi, 2006).

After validating the scales, associations between HL, HN and malaria-related behaviours were examined. Behaviours measured on five-point scales (bednet use, prompt treatment-seeking for self, prompt treatment-seeking for family, medication adherence, asking healthcare practitioners questions) were dichotomised (consistent behaviour defined as Yes: Always/Often = 1; inconsistent behaviour defined as no: Sometimes/Rarely/Never = 0). Behaviours originally measured as binary outcomes, indoor spraying, and bush clearing, were retained in their original form. Dosage knowledge, also measured as a binary outcome, was examined both as an outcome of HL/HN and as a potential mediator in relationships between HL/HN and malaria behaviours.

Associations between each behaviour and HL and HN were first assessed bivariately. Chi-square tests and Kruskal-Wallis tests were applied to the HL scale, and ANOVA was used for the HN scale. Behaviours showing no evidence of association with HL or HN, defined as p-values above 0.1, were excluded from subsequent multivariable analyses. Binary logistic regression was used to model the probability of each individual practising a given behaviour for binary outcomes. The response Y_i follows a Bernoulli distribution, taking the value 1 if the behaviour is practised and 0 otherwise. The probability that individual i engages in the behaviour is denoted $P_i = \Pr(Y_i = 1)$. The binary logistic regression model is given as:

$$Logit(P_i) = \log\left(\frac{P_i}{1 - P_i}\right) = \beta_1 \mathrm{X} + \sum_{i=1}^{n} \beta_i Z_i \tag{3}$$

Where X represents HN or HL, β's are the parameters to be estimated and Z_i represents the control variables included in the model.

Then, as a robustness check, behaviours measured on five-point scales, including bed net use, prompt treatment seeking for self and family, medication adherence, and asking healthcare practitioners questions, were treated as ordered categorical outcomes and analysed using ordered logistic regression, preserving the full ordinal structure (Always, Often, Sometimes, Rarely, Never). The ordered logistic regression model was specified as:

$$Logit[P(Y_i \leq j)] = \log\left(\frac{P(Y_i \leq j)}{P(Y_i > j)}\right) = \beta_i \mathrm{X}_i + \alpha_j \tag{4}$$

Where; Y_i represents the ordinal malaria behaviour for observation i, X represents HN or HL, and Z_i represents the control variables included in the model. j =1, 2, 3, 4, α_j = threshold/cutpoint parameters (4 cutpoints for 5 categories), X_i = vector of independent variables for observation i, including HN and HL, and β_i represents the regression coefficients for the independent variables. Both analytical approaches (ordered and binary) were applied to the ordinal-scale behaviours to assess whether associations with HL and HN were robust to measurement strategy. Results are presented as average marginal effects (AMEs) for binary outcomes, representing percentage-point changes in the predicted probability of practising each behaviour per one-unit increase in HL or HN (Williams, 2012), and as odds ratios for ordered outcomes. AMEs, also referred to as average predicted probabilities, were estimated to quantify the relationship between health literacy, health numeracy, and each malaria-prevention behaviour (Gelman & Hill, 2007).

The regression models were adjusted to control for relevant covariates. These were selected based on the Social Determinants of Health (SDOH) framework (Solar & Irwin, 2010) and the Health Literacy Skills Framework (Squiers et al., 2012). The SDOH framework identifies structural and intermediary determinants of health outcomes. At the same time, the Health Literacy Skills Framework specifically explains how individual characteristics, socioeconomic factors, health system access, community resources, and information sources can influence the relationship between HL, HN, and behaviours. Specifically, we controlled for: Demographic factors (age, sex, and recent malaria exposure); Socioeconomic factors (education level, source of health information, and employment status); residence; and Health environment factors (health insurance status, proximity to health facilities, and availability of community health resources). All models were estimated with robust standard errors.

C.3 Results

C.3.1 Descriptive Analysis

Results in Table C.1 show that respondents averaged 6.12 out of 10 in HN with a deviation of 2.85. The total score of the dichotomised scale was calculated (0 to 16 points), with higher scores indicating better HL. The HL score had a mean of 12.2 and a standard deviation of 4.2. The total score was then categorised into "sufficient" (13 to 16 points), "problematic" (9 to 12 points), and "inadequate" (0 to 8 points) (Rouquette et al., 2018). The majority (60%) of respondents had sufficient HL, while nearly one-fifth (17%) had inadequate HL, and 23 per cent had problematic HL. Preventive behaviours showed varied findings: just over half of participants (51%) reported bednet use, 42 per cent benefited from indoor residual spraying, and a majority (87%) engaged in bush-clearing activities around their homes. However, for treatment- seeking behaviours, only 31 per cent sought treatment promptly for themselves and 32 per cent for family members.

Treatment adherence was reported by just over half (54%) of participants, while patient engagement with healthcare providers was moderate, with 42 per cent indicating they asked questions during consultations. Additionally, 63 per cent demonstrated adequate knowledge of proper medication dosing. In terms of gender, females comprised 52 per cent of the sample, with most respondents residing in urban areas (73%), and 59 per cent working either employed or self-employed. Educational attainment shows that only 3 per cent reported no exposure to formal schooling. Individuals aged 45 years and above had the highest relative representation at 30 per cent, compared with 20 to 26 per cent in the other groups. Nearly all respondents (98%) knew what transmits malaria, slightly over one third (32%) reported recent malaria exposure, and 80 per cent were insured.

Most respondents demonstrated strong knowledge of common malaria symptoms, with fever (89.5%), headache (86.3%), muscle pain (82.9%), and fatigue (79.2%) being the most frequently mentioned, while fewer than two-thirds identified loss of appetite (58.3%). The highest percentage of responses regarding knowledge of prevention methods was for sleeping under bed nets (96.2%), followed by mosquito repellents (67.9%) and eliminating breeding sites (62.1%), while half mentioned taking anti-malarial medication (50.2%).

Table C.1: Descriptive Analysis

Variables	Obs	Mean	Std. Dev.	Min	Max
HN score	511	6.12	2.85	0	10
HL score	504	12.2	4.2	0	16
Bednet Use	508	0.51	0.49	0	1
Indoor Residual Spraying (IRS)	505	0.42	0.49	0	1
Bush Clearing	505	0.87	0.34	0	1
Treatment seeking-self	507	0.31	0.46	0	1
Treatment seeking-family	507	0.32	0.47	0	1
Treatment adherence	507	0.54	0.36	0	1
Asking questions	500	0.42	0.43	0	1
Dosing knowledge	506	0.63	0.48	0	1
Rural residence	511	0.27	0.44	0	1
Working	510	0.59	0.49	0	1
Female	511	0.52	0.50	0	1
Use formal sources of information	511	0.95	0.21	0	1
Insured	511	0.80	0.40	0	1
Health Literacy (HL)					
Inadequate HL	504	0.17	0.38	0	1
Problematic HL	504	0.23	0.42	0	1
Sufficient HL	504	0.60	0.49	0	1
Education					
No education	510	0.03	0.16	0	1
Primary Education	510	0.18	0.38	0	1
Some Secondary Education	510	0.68	0.47	0	1
Tertiary Education	510	0.11	0.32	0	1

Table C.1: Continued

Variables	Obs	Mean	Std. Dev.	Min	Max
Age					
15-24	511	0.20	0.40	0	1
25-34	511	0.26	0.44	0	1
35-44	511	0.23	0.42	0	1
45+	511	0.30	0.46	0	1
Proximity to Health centres					
Less than 1km	497	0.18	0.39	0	1
1km to 3 km	497	0.27	0.44	0	1
3km to 5km	497	0.19	0.39	0	1
Above 5 km	497	0.36	0.48	0	1
Knowledge of malaria transmission	511	0.98	0.16	0	1
Recent Malaria Exposure	510	0.32	0.47	0	1

Characteristic	n	percent
Knowledge of malaria symptoms*		
Fever	451	89.5
Headache	435	86.3
Muscle Pain	418	82.9
Fatigue	399	79.2
Loss of Appetite	294	58.3
Diarrhoea	69	13.7
Other Symptoms	42	8.3
Knowledge of malaria Prevention methods*		
Sleeping under bed nets	485	96.2
Using Mosquito repellents	342	67.9
Taking anti-malarial medication	253	50.2
Eliminating mosquito breeding sites	313	62.1
Others	6	1.2

Note: Variations in totals due to missing values, *Variables capture multiple responses

C.3.2 Validation of Health Literacy and Numeracy Scales

C.3.2.1 Validation of the Health Literacy Scale

Floor and Ceiling effects

For the 4-point likert scale items, fourteen respondents (2.78%) obtained the lowest possible score of 16, while two respondents (0.40%) achieved the maximum score of 64. Both percentages fall well below the commonly accepted 15 per cent cutoff, indicating no floor or ceiling effects. For the dichotomised scale, however, a ceiling effect was observed, with 129 respondents (25.6%) scoring the maximum of 16, while no floor effect was observed, as only 2.78 per cent scored the minimum.

Distribution of HL Responses

Table C.2 shows the responses for the individual items of the HL scale. Over two-thirds found it easy to understand doctors' explanations (68.2%), follow instructions on prescribed medicines (72.6%), make decisions based on doctor guidance (73.5%) and understand advice on health from family members or friends (70.5%). Mean scores for these tasks ranged from 1.91 to 2.09, indicating overall ease. In contrast, accessing and applying information on mental health and health screening was more challenging. Fewer than half found it easy or very easy to find information on managing mental health (44.7%; average of 2.63), and slightly more than half of respondents understood why health screenings are needed (55.7%; average of 2.42). Judging the reliability of health information in the media and deciding how to protect oneself based on media sources were also moderately difficult (mean 2.24-2.30).

Table C.2: Distribution of Responses to the Health Literacy Scale

On a scale from very easy to very difficult, how easy would you say it is to... (%)	Very easy	Easy	Difficult	Very difficult	mean	SD
1. Find information on treatments of illnesses that concern you?	20.23	61.09	16.15	2.53	2.01	0.68
2. Find out where to get professional help when you are ill?	20.62	59.34	17.32	2.72	2.02	0.70
3. Understand what your doctor says to you?	17.54	68.23	12.87	1.36	1.98	0.60
4. Understand your doctor's or pharmacist's instructions on how to take a prescribed medicine?	18.45	72.62	7.96	0.97	1.91	0.54
5. Judge when you may need to get a second opinion from another doctor?	12.43	60.97	24.27	2.33	2.17	0.66
6. Use information the doctor gives you to make decisions about your illness?	13.23	73.54	12.06	1.17	2.01	0.55
7. Follow instructions from your doctor or pharmacist?	18.91	72.32	7.8	0.97	1.91	0.55
8. Find information on how to manage mental health problems like stress or depression?	7.39	37.35	39.88	15.37	2.63	0.83
9. Understand health warnings about behaviour such as smoking, low physical activity and drinking too much?	18.52	59.06	19.69	2.73	2.07	0.70
10. Understand why you need health screenings?	10.55	45.12	35.94	8.4	2.42	0.79
11. Judge if the information on health risks in the media is reliable?	9.59	54.79	31.31	4.31	2.30	0.70
12. Decide how you can protect yourself from illness based on information in the media?	10.51	58.95	27.04	3.5	2.24	0.68
13. Find out about activities that are good for your mental well-being?	13.4	65.24	18.64	2.72	2.11	0.65
14. Understand advice on health from family members or friends?	11.07	70.49	17.09	1.36	2.09	0.57
15. Understand information in the media on how to get healthier?	10.87	66.8	18.64	3.69	2.15	0.65
16. Judge which everyday behaviour is related to your health?	9.55	67.64	19.69	3.12	2.16	0.63

Reliability and dimensional structure of the HL scale

Internal consistency was high, with Cronbach's alpha of 0.924 and McDonald's omega of 0.929. Bartlett's test of sphericity was significant, with a chi-square value of 4609.123, $p < 0.001$, and the Kaiser-Meyer-Olkin (KMO) value was 0.929, confirming suitability for factor analysis. The corrected item-total correlations were high, ranging from 0.53 to 0.78. Exploratory factor analysis using principal component extraction identified a single dominant factor with an eigenvalue of 7.7, accounting for 49.0 per cent of the total variance. The second component had an eigenvalue of 1.5, explaining about 10.0 per cent of variance, with all subsequent components having eigenvalues below 1. Factor loadings on the first component ranged from 0.50 to 0.79 (Table C.20 in the appendix), with all 16 items loading strongly and positively, supporting the unidimensional structure of the HL scale in the Gabonese context. The scree plot showed a clear break after the first component, supporting retention of a single factor (Figure C.3 in the appendix).

IRT analysis of the HL scale

IRT analysis was conducted on the dichotomised items to examine item difficulty and model fit. Table C.3 shows that the Loevinger's H coefficients exceeded 0.30 for all items, indicating acceptable scalability. This supports the monotonicity of item responses and provides evidence that the scale is sufficiently unidimensional to justify summing item scores (Hardouin et al., 2011). Local independence, as measured by Yen's Q3 statistic, showed that only two item pairs exceeded an absolute threshold of 0.30. Items 3 and 4 showed a residual correlation of 0.38, both addressing comprehension of provider communication, while items 11 and 12 had a residual correlation of 0.44, focusing on appraisal and use of media-based health information. These two pairs represent 1.7 per cent of all item pairs, supporting the scale's essential unidimensionality and allowing valid interpretation of total scale scores.

Item difficulty parameters ranged from -1.67 to 0.16, indicating clear differences across HL domains. Healthcare interaction tasks showed the lowest item difficulty: following prescribed medicine instructions (difficulty: -1.67), understanding doctor explanations for medicines (difficulty: -1.66), understanding doctor explanations (difficulty: -1.30), and making decisions based on doctor guidance (difficulty: -1.35). In contrast, health promotion and prevention literacy tasks proved substantially more challenging. Accessing mental health information was the most difficult item (difficulty: 0.16), followed by understanding the rationale for health screenings (difficulty: -0.16). The critical appraisal skills of judging media information reliability (difficulty: -0.43) and deciding protective actions based on media (difficulty: -0.59) occupied intermediate difficulty levels.

Table C.3: IRT-Based Item Analysis and Loevinger H Coefficients of the Health Literacy Scale.

Item	**Difficulty**	**Loevinger H coeff**
1. Find information on treatments of illnesses that concern you?	-1.06	0.42
2. Find out where to get professional help when you are ill?	-1.01	0.50
3. Understand what your doctor says to you?	-1.30	0.53
4. Understand your doctor's or pharmacist's instructions on how to take a prescribed medicine?	-1.66	0.69
5. Judge when you may need to get a second opinion from another doctor?	-0.75	0.49
6. Use information the doctor gives you to make decisions about your illness?	-1.35	0.56
7. Follow instructions from your doctor or pharmacist?	-1.67	0.73
8. Find information on how to manage mental health problems like stress or depression?	0.16	0.64
9. Understand health warnings about behaviour such as smoking, low physical activity and drinking too much?	-0.91	0.51
10. Understand why you need health screenings?	-0.16	0.59
11. Judge if the information on health risks in the media is reliable?	-0.43	0.60
12. Decide how you can protect yourself from illness based on information in the media?	-0.59	0.58
13. Find out about activities that are good for your mental well-being?	-0.94	0.54
14. Understand advice on health from family members or friends?	-1.08	0.46
15. Understand information in the media on how to get healthier?	-0.90	0.56
16. Judge which everyday behaviour is related to your health?	-0.88	0.51
Discrimination	2.42	

Table C.12 in the appendix shows the results of the DIF analysis for the HL scale across education, sex, and age. Most items showed no significant DIF across any group or method. A few items, including "Find out where to get professional help when you are ill?" and "Understand advice on health from family members or friends", showed significant DIF for sex and education, respectively, in both methods. However, estimated item difficulties were identical across groups for these items, indicating no meaningful differences in item functioning.

Known-Groups Validity analysis

The associations between HL levels and study characteristics (age, education, sex, residence, employment, and sources of health information) are presented in Table C.4. Statistically significant associations were observed for education ($p<0.001$ for both chi-square and Kruskal-Wallis tests), residence ($p<0.05$ for Kruskal-Wallis tests), and use of formal health information sources ($p<0.05$ for both tests). Employment was significantly associated with categorised levels of HL. Inadequate HL was highest among participants with no formal education (40%) and lowest among those with tertiary education (10.5%). Inadequate HL was more common in rural areas (23.5%) than in urban areas (14.7%), and among participants without formal health information sources (37.5%) than among those using formal sources (15.8%). No significant associations were observed for sex and age.

Table C.4: Known Groups Validity of the Health Literacy Scale

Characteristics	Inadequate HL	Problematic HL	Sufficient HL	Chi^2 p-value[a]	Kruskal-Wallis[b] (HL score)
Education (%)					
None	40.0	26.6	33.3		
Primary	39.3	21.3	39.3	48.67 p <0.000	25.40 p =0.000
Secondary	11.4	23.1	65.5		
Tertiary	10.5	26.3	63.2		
Sex					
Female	19.7	21.6	58.7	2.77 p = 0.251	0.74 p =0.389
Male	14.4	25.1	60.5		
Residence					
Urban	14.7	23.9	61.4	5.50 p = 0.064	8.10 p =0.004
Rural	23.5	21.3	55.2		
Employment					
Not working	24.5	17.8	57.7	16.22 p <0.000	0.63 p =0.426
Working	11.9	27.1	61.0		
Age					
15-24	13.7	28.5	57.8		
25-34	12.2	21.4	66.4	12.20 p =0.058	5.26 p =0.154
35-44	16.8	27.7	55.5		
45+	23.7	17.8	58.5		
Source of Health Information				10.78 p =0.005	9.69 p =0.002
No formal sources	37.5	16.7	45.8		
Uses formal sources	15.8	23.4	60.2		

Note: [a]Chi-square test for categorical variables; [b]Kruskal-Wallis tests

C.3.2.2 Validation of the HN scale

Reliability and Classical Test Theory (CTT) Item Analysis

The results for the HN scale supported its reliability, with a KR-20 coefficient of 0.81. CTT item analysis in Table C.6 showed adequate item performance. Item difficulty, measured as the proportion of correct responses, ranged from 0.40 to 0.78, indicating an appropriate spread of item difficulty levels. Item discrimination, assessed using item total score correlations, ranged from 0.45 to 0.68, with all values positive and statistically significant. These results indicate that the items effectively differentiated between respondents with lower and higher levels of HN.

IRT analysis of the HN scale

The Loevinger H coefficients for individual items ranged from 0.31 to 0.51 in Table C.5, with an overall scale coefficient of 0.42, all above the minimum threshold of 0.30, indicating acceptable scalability. Monotonicity was confirmed, with no items exceeding critical values of 40, indicating that the probability of a correct response increased appropriately with higher levels of the latent trait. Local independence using Yen's Q3 was generally satisfied, with only one item pair (randomisation and reading a table) slightly exceeding the Q3 threshold (0.302). This pair represents only about 2.2 per cent of all item pairs, supporting the scale's essential unidimensionality and justifying the interpretation of total scale scores. This supports the scale's suitability for IRT modelling.

Table C.5 shows that most items did not display significant DIF. A few questions, such as questions 2, 7, 8, and 9, showed marginal significance in either the logistic regression or the Mantel-Haenszel tests; however, these effects were inconsistent across methods, suggesting that the differences are not meaningful. Overall, the results indicate minimal item bias, with the scale performing similarly across the examined subgroups. To assess the suitability of either a one-parameter or a two-parameter IRT model for item analysis, log-likelihood ratio tests were conducted to compare the fit of the two models. The chi-square statistic was 59.77, with the null hypothesis of no difference between the one- and two-parameter models rejected at $p < 0.001$, indicating that the two-parameter model provided a statistically significant improvement in fit over the one-parameter model. The three-parameter model (including a guessing parameter) was not estimated because respondents were instructed to leave items blank rather than guess when they did not know the answer.

Table C.5: Item Scalability Coefficients and DIF of the Health Numeracy Scale

			Logistic Regression				**Mantel-Haenszel**			
Questions		**Hi**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
1	Range/Blood sugar goal in a diabetic	0.43	N	N	N	N	N	N	N	N
2	Scale/Reporting pain	0.31	*	N	N	N	N	*	N	N
3	Ordering numbers/Test results	0.39	N	N	N	N	N	N	N	N
4	Randomisation/Study participation	0.51	N	N	N	N	N	N	N	N
5	Calculating probability/Screening tests	0.44	N	N	N	N	N	N	N	N
6	Uncertainty/95% CI of treatment efficacy	0.44	N	N	N	N	N	N	N	N
7	Interpreting decimals/Reading a digital thermometer	0.34	N	N	N	N	N	N	N	*
8	Reading a table/Interpreting a nutrition label	0.42	N	N	*	*	N	N	N	N
9	Interpreting survival curve/Survival estimates	0.43	N	N	*	N	N	N	N	N
10	Small risk formats/Pictogram	0.36	N	N	N	N	N	N	N	N
	Overall Scale	**0.41**								

Note*:* Hi = Loevinger H coefficient, item scalability coefficient. 1-Education; 2-Literacy level; 3-Age group; 4-Sex: N-No significant DIF detected; *= Significant DIF detected

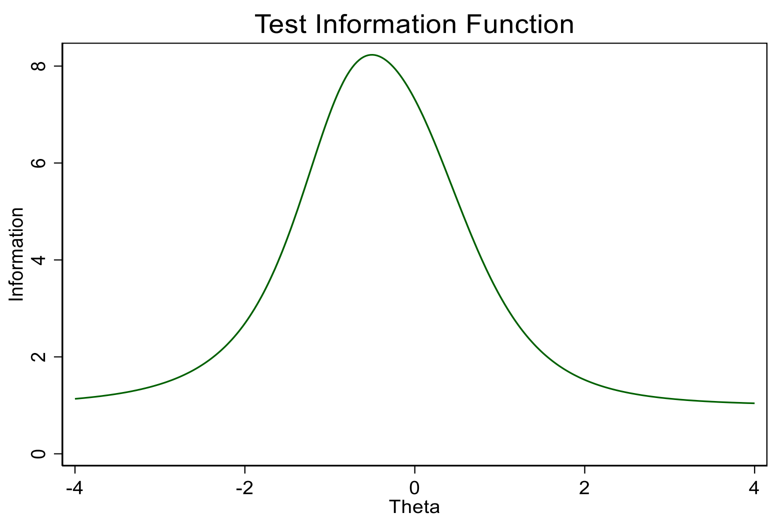
The IRT parameters indicate a range in the difficulty parameter. The results in Table C.6 show that the Item difficulty estimates ranged from -1.52 to 0.47, indicating that most items were easy (negative values), and the most challenging item was a pictogram representing small risks, with a value of 0.49. The pain reporting scale item emerged as the easiest (-1.52). Discrimination parameters ranged from 0.98 to 2.82, indicating acceptable discrimination. The TIF reaches its maximum at an ability level between -1 and 0, indicating that the test provides the greatest amount of information and the best discriminative capacity at an ability level slightly below the average for the target population (see Figure C.1).

Table C.6: Item-Level Analysis of the Health Numeracy Scale

Items		CTT		IRT	
		Difficulty 0 to 1	**Discrimination 0 to 1**	**Difficulty -3.0 to 3.0**	**Discrimination 0 to 3.0**
1	Range/Blood sugar goal in a diabetic	0.73	0.62	-0.85	1.82
2	Scale/Reporting pain	0.78	0.45	-1.52	0.98
3	Ordering numbers/Test results	0.60	0.62	-0.36	1.80
4	Randomisation/Study participation	0.76	0.68	-0.81	2.82
5	Calculating probability/Screening tests	0.51	0.67	-0.04	2.26
6	Uncertainty/95% CI of treatment efficacy	0.46	0.63	0.14	1.98
7	Interpreting decimals/Reading a digital thermometer	0.67	0.56	-0.73	1.25
8	Reading a table/Interpreting a nutrition label	0.67	0.65	-0.61	1.83
9	Interpreting survival curve/Survival estimates	0.53	0.66	-0.11	1.88
10	Small risk formats/Pictogram	0.40	0.51	0.47	1.00

Notes: CTT Difficulty: Classical test theory difficulty calculated as % correct; CTT Discrimination calculated as item-total correlation. IRT Difficulty and Discrimination: Item response theory parameters determined by a two-parameter model.

Figure C.1: Test Information Function



Known-groups Validity of the HN scale

Table C.7 shows that respondents with higher education levels, urban residence, and sufficient HL had significantly higher mean HN scores and theta values (all $p < 0.001$). Those without formal education had an average score of 2.43, while individuals with primary and secondary education levels had averages of 4.77 and 6.57, respectively. Urban residents scored higher than their rural counterparts, with an average score of 6.51 versus 5.05. Age also showed significant differences in HN, with middle-aged adults (25 to 44 years) achieving the highest scores; sex, however, showed no significant differences ($p>0.05$). HL was associated with HN, as participants with inadequate HL scored lower than those with problematic or sufficient levels. The scale scores correlated strongly with ability estimates ($r = 0.987$, $p < 0.001$), indicating strong internal consistency.

Table C.7: Differences in Health Numeracy and Associations by Various Characteristics

	NUMi Score Number of Items Correct		**Ability Score (Θ) Mean (SD)**	
Characteristics	**Mean (SD)**	**F, p-value**	**Mean (SD)**	**F, p-value**
Education (%)				
None	2.43 (1.9)		-1.09 (0.6)	
Primary	4.77 (3.2)	19.62 p =0.000	-0.42 (0.9)	18.63 p =0.000
Secondary	6.57 (2.6)		0.15 (0.8)	
Tertiary	6.40 (2.4)		0.03 (0.7)	
Sex				
Female	6.03 (2.9)	0.39 p =0.533	-0.04 (0.9)	0.60 p =0.438
Male	6.18 (2.8)		0.02 (0.9)	
Residence				
Urban	6.51 (2.7)	27.75 p =0.000	0.12 (0.9)	25.96 p =0.000
Rural	5.05 (2.9)		-0.32 (0.9)	
Age				
15-24	5.98 (2.4)		-0.05 (0.7)	
25-34	6.49 (2.8)	3.49 p =0.016	0.11 (0.9)	3.39 p =0.018
35-44	6.52 (2.8)		0.13 (0.9)	
45+	5.58 (3.1)		-0.16 (1.0)	
Health Literacy				
Inadequate	5.69 (3.4)	9.78 p =0.000	-0.09 (1.0)	9.11 p =0.000
Problematic	5.31 (3.0)		-0.26 (0.9)	
Sufficient	6.56 (2.5)		0.13 (0.8)	
Correlation with Theta= 0.987, p=0.000				

Note: Theta (θ) is the latent trait ability of the respondent as determined by responses to the items and the IRT model. Analysis based on the total score of HN out of 10

The validation analyses indicate that both the HL and HN scales are reliable and valid instruments, suitable for use in further analyses.

C.3.3 Behavioural Differences across Health Literacy and Numeracy

Having established the psychometric properties of both the HL and HN measures, we examined their associations with behaviours related to malaria prevention and treatment. We hypothesised that individuals with better HL and HN would demonstrate engagement in malaria control behaviours. This section presents analyses examining associations between the validated HL and HN scales and the malaria prevention and control behaviours, including bed net use, indoor residual spraying, bush clearing, treatment-seeking for self and family, treatment adherence, patient engagement, and dosing knowledge.

Behavioural differences across HL

Table C.8 shows observed variations in behaviours by HL. Prompt treatment-seeking for self and family, dosing knowledge, medication adherence, and engagement with healthcare providers by asking questions were all significantly associated with HL ($p<0.05$ for both tests). 66 per cent of respondents with correct dosing knowledge had sufficient HL compared with 48.6 per cent among those without; and 65.4 per cent of those who always or often asked healthcare providers questions had sufficient HL compared with 41.5 per cent among those who rarely or never asked. Indoor spraying was significant by chi-square ($p<0.001$) but not by HL score ($p=0.665$). Regular bednet use and bush clearing showed no significant association with HL, and these behaviours were excluded from subsequent analyses. Table C.13 in the appendix reveals similar patterns when the analysis focused on ordered categorical assessments of behaviours with associations with medication adherence and engagement with health care practitioners by asking questions.

Table C.8: Variations in Health Behaviours by Health Literacy (Binary Outcomes)

Malaria Behaviour		HL Categories				HL score
		Inadequate HL	Problematic HL	Sufficient HL	Chi^2 p-value[a]	Kruskal-Wallis[b] (HL score)
Regular Bednet use	Yes	17.69	21.09	61.22	1.95 p=0.376	1.05 p=0.306
	No	16.67	26.47	56.86		
Prompt treatment-seeking (self)	Yes	20.00	17.85	62.15	16.38 p<0.001***	5.37 p=0.021**
	No	12.21	33.14	54.65		
Indoor spraying	Yes	10.10	32.21	57.69	23.13 p<0.001***	0.19 p=0.665
	No	22.30	16.72	60.98		
Medication adherence	Yes	17.38	20.24	62.38	13.49 p=0.001**	9.71 p=0.002**
	No	16.88	38.96	44.16		
Bush Clearing	Yes	16.71	23.67	59.63	1.02 p=0.600	0.04 p=0.842
	No	20.31	18.75	60.94		
Prompt treatment-seeking (family)	Yes	18.64	18.34	63.02	13.71 p= 0.001**	7.31 p=0.007**
	No	14.47	33.33	52.20		
Asking questions	Yes	13.62	20.98	65.40	24.47 p<0.001***	29.12 p<0.001***
	No	29.27	29.27	41.46		
Dosing knowledge	Yes	12.70	21.27	66.03	17.13 p<0.001***	21.89 p<0.001***
	No	24.86	26.52	48.62		

Notes: [a]Chi-square test examines the association between categorical HL levels (inadequate/ problematic/ sufficient) and binary behaviours (yes/no). [b]Kruskal-Wallis test examines the association between continuous HL score (0-16 points) and binary behaviours. ***, **, * significant at the 1, 5, and 10%-level respectively. Behaviours dichotomised as: Yes (always/often) vs. No (sometimes/rarely/never)

Behavioural differences across HN

Behavioural differences by HN were assessed using ANOVA, and the results are presented in Table C.9. Prompt treatment-seeking for oneself was significantly associated with higher numeracy scores (mean 6.62) among those who sought timely care, compared to those who did not (mean 5.17). Similarly, prompt treatment-seeking among family members showed significant associations, with those who sought timely care for relatives scoring higher (6.52 versus 5.26). For indoor spraying, those who did not engage in the practice scored higher (6.83 versus 5.09). Asking questions during healthcare encounters also showed a significant association, with those who asked scoring higher (6.39 versus 5.31). Conversely, bednet use, dosing knowledge, and bush clearing demonstrated no significant relationships with HN (p>0.05). Dosage completion was significant at the 10 per cent level of significance (F=3.49, p=0.062). Analyses of behaviours measured on the ordinal scales indicated significant associations with HN scores for all behaviours: bednet use, prompt treatment-seeking for self and family members, medication adherence, and asking questions of healthcare providers (p<0.001), as examined in Table C.14 in the appendix.

Table C.9: Variations in Health Behaviours by Health Numeracy (Binary Outcomes)

Malaria Behaviour	Mean (SD)	ANOVA (F: p-value)
Bednet use		
Yes	6.04 (2.9)	0.61, p=0.435
No	6.24 (2.8)	
Prompt treatment-seeking (self)		
Yes	6.62 (2.8)	31.26, p=0.000***
No	5.17 (2.7)	
Indoor spraying		
Yes	5.09 (2.7)	50.09, p=0.000***
No	6.83 (2.7)	
Dosage completion		
Yes	6.22 (2.9)	3.49, p=0.062*
No	5.57 (2.4)	
Bush Clearing		
Yes	6.08 (2.9)	0.47, p=0.491
No	6.34 (2.6)	
Prompt treatment-seeking (family)		
Yes	6.52 (2.9)	22.23, p=0.000***
No	5.26 (2.6)	
Asking questions		
Yes	6.39 (2.8)	13.44, p=0.000***
No	5.31 (2.9)	
Dosing knowledge		
Yes	6.02 (2.9)	0.96, p=0.326
No	6.28 (2.6)	

Notes: Analysis based on the total score calculated as a sum across all items (0 to 10). ***, **, * significant at the 1, 5, and 10%-level respectively.

C.3.4 Regression Analysis of Health Literacy, Numeracy and Health Behaviours

Table C.10 shows that higher HL was significantly associated with medication adherence, asking healthcare practitioners questions, and having dosage knowledge. A one-point increase in the HL scale is associated with a 2.2 to 2.3 percentage-point increase in the probability of dosing knowledge, a 1.8 to 2.1 percentage-point increase in the probability of asking health care providers questions, and an increase of 0.8 to 1.3 percentage points in the probability of medication adherence. Similar results are observed in Tables C.15 and C.16 in the appendix, where HL is modelled using categorical levels rather than the continuous score and behaviours are analysed as ordered outcomes. A one-point increase in HL increases the odds of moving to a higher category of asking questions by approximately 9 to 12 per cent, and medication adherence by 7 to 9 per cent. Similarly, individuals with sufficient HL had significantly higher odds of adherence to medication and greater engagement with healthcare providers through asking questions compared to those with inadequate HL. Indoor spraying also showed a positive association, with increased odds among those with sufficient HL compared with inadequate HL. Prompt treatment-seeking (self and family) showed non-significant associations.

Table C.10: Regression Analysis of Health Literacy and Malaria Control Behaviours (Binary Outcomes)

	HL		
Malaria Behaviour	**AME[a] [95% CI]**	**AME[b] [95% CI]**	**AME[c] [95% CI]**
Prompt treatment-seeking (self)	0.0002 [-0.009,0.009]	0.005 [-0.005,0.015]	0.004 [-0.006,0.015]
Indoor spraying	0.010 [-0.0001,0.019]	0.006 [-0.004,0.015]	0.006 [-0.004,0.015]
Medication adherence	0.008** [-0.001,0.014]	0.013** [0.005,0.020]	0.013** [0.005,0.022]
Prompt treatment-seeking (Family)	0.003 [-0.005,0.012]	0.007 [-0.003,0.017]	0.007 [-0.003,0.017]
Asking questions	0.021*** [0.013,0.028]	0.019*** [0.011,0.028]	0.018*** [0.009,0.027]
Dosage knowledge	0.023*** [0.014,0.032]	0.023*** [0.013,0.032]	0.022*** [0.013,0.032]

Notes: ***, **, * significant at the 1, 5, and 10%-level, respectively. [a]unadjusted coefficients. [b]Coefficients adjusted for age, sex, residence, employment, recent malaria exposure, insurance status, proximity to health centres, source of health information, and availability of community health resources (including malaria prevention programs). [c]additionally adjusts for education level. All models were estimated using robust standard errors. CI: confidence interval. AME = Average Marginal Effects and represent changes in predicted probability of the behaviours per one-unit increase in HL. Analysis based on binary measures of the malaria behaviours.

Regression analysis for HN

The results in Table C.11 show that higher HN was associated with improved malaria-related behaviours in the binary models. Individuals with greater numeracy were more likely to seek prompt treatment for themselves and their family, with unadjusted increases of 3.8 per cent and 3.2 per cent, respectively, and adjusted increases of 1.4 per cent to 1.7 per cent after accounting for age, sex, residence, employment, proximity to health centres, source of health information, insurance status, recent malaria exposure, and education. However, HN was inversely associated with indoor spraying, indicating that more numerate individuals were less likely to use this preventive measure. For treatment adherence and asking questions, the likelihood of these behaviours increased with higher HN scores, though the effect disappeared when education was included in the model. Results of the ordinal outcomes in Table C.17 in the appendix show that higher HN increases the odds of moving into a higher frequency category of prompt treatment-seeking for self and family, indicating a greater likelihood of engaging in the behaviour always, although the effect sizes for treatment-seeking for family members were smaller. Higher HN was associated with lower odds of indoor spraying, implying a lower likelihood of moving toward more frequent engagement in this behaviour. In contrast, higher HN reduced the odds of being in a higher category of treatment adherence. Asking healthcare providers questions showed no significant association with HN.

Table C.11: Regression Analysis of Health Numeracy and Malaria Control Behaviours (Binary Outcomes)

Malaria Behaviour	Health Numeracy		
	AME[a] (95% CI)	AME[b] (95% CI)	AME[c] (95% CI)
Prompt treatment-seeking (self)	0.038*** [0.026, 0.050]	0.017** [0.003, 0.031]	0.016** [0.001, 0.030]
Indoor spraying	-0.050*** [-0.062, -0.037]	-0.032*** [-0.046, -0.018]	-0.037*** [-0.051, -0.022]
Treatment Adherence	0.010** [0.001, 0.020]	0.010* [-0.002, 0.021]	0.009 [-0.003, 0.020]
Prompt treatment-seeking (family)	0.032*** [0.020, 0.044]	0.014* [-0.001, 0.028]	0.013* [-0.002, 0.028]
Asking questions	0.023*** [0.011, 0.035]	0.014* [-0.001, 0.028]	0.009 [-0.006, 0.024]

Notes: ***, **, * significant at the 1, 5, and 10%-level respectively. Coefficients estimated using robust standard errors. [a]Unadjusted Coefficients, [b]adjusted for age, sex, residence, employment, proximity to health centres and source of health information and recent malaria exposure. [c]education level. CI: confidence interval. AME: Average Marginal Effects, and they represent changes in the predicted probability of the behaviours per one-unit increase in the HN. Analysis based on Binary measures of the malaria behaviours and estimated using robust standard errors.

C.3.5 Discussion

Our study validated measures of HN and HL in Gabon and examined their relationship with malaria-control behaviours. Both HL and HN scales demonstrated strong reliability with minimal local dependence, supporting the validity of using total scale scores in subsequent analyses. Item discrimination and difficulty parameters confirmed that the scales appropriately captured variation in the sample. Differential item functioning analyses indicated that a few items were influenced by sex or education, but these differences did not translate into meaningful differences in item functioning of both scales. Our HN scale is one of the few available tools for assessing HN in African settings, providing a practical method for measuring an important aspect of health education that is generally low there (Gatobu et al., 2022; McClintock et al., 2020). Item-level response patterns revealed differential difficulty across HL domains, with healthcare interaction tasks, such as following medical instructions, considerably easier than health promotion tasks, such as accessing mental health information. This suggests that literacy competencies vary across domains rather than being uniform. The level of sufficient HL (60%) is comparable to that reported in a Swiss study (Meier et al., 2022), which also reported sufficient levels of HL. However, they differ from previous studies, in which a high percentage of the sample had insufficient levels of HL (Liu et al., 2023). No statistically significant differences in HL levels were observed across age groups. This finding contrasts with the results in Europe, where older people had insufficient literacy levels (Sørensen et al., 2015). Exploratory factor analysis of the 16 items of the French HLS-EU-Q16 items determined a single factor structure accounting for 49 per cent of the total variance, consistent with validations in Sweden using the Arabic version of the instrument (Bergman et al., 2023) as well as Swedish parents with infant children (Mekhail et al., 2022). However, the results differ from those in Bangladesh (Mousum et al., 2024) and Romania (Coman et al., 2022), where three- and four-factor structures were found, respectively. This demonstrates that the HL dimensions of the scale manifest themselves differently across cultures.

Regarding Malaria control behaviours, individuals with higher HL and HN scores showed better behaviours. Both HN and HL had significant positive associations with engagement and question-asking behaviour during healthcare encounters and treatment adherence. Patients with higher literacy and numeracy skills are able to understand, interpret, and act on health information, making them more confident in interacting with healthcare providers and learning about medical conditions and treatments (Hibbard et al., 2007; Katz et al., 2007; Smith et al., 2013). Numeracy encompasses not only computational skills but also the ability to interpret quantitative health information and apply numerical concepts to dates, times, and medical schedules (Schapira et al., 2008). Individuals with stronger numeracy may therefore feel more confident engaging with healthcare providers, requesting clarification of numerical health information, and participating actively in treatment decisions.

The positive association of treatment adherence is consistent with literature demonstrating that individuals with higher HL and HN better understand medication instructions, recognise the importance of completing prescribed courses, and are more likely to adhere to treatment regimens (Gazmararian et al., 2006; Ngoatle & Mothiba, 2021; Persell et al., 2020). However, it contradicts the findings of Sawkin et al. (2015), who found no association between literacy levels and treatment adherence. The association between HL and dosing knowledge highlights that literacy enables individuals to understand and correctly apply treatment instructions. This finding aligns with previous research demonstrating that HL enables individuals to understand better and implement preventive health measures (Berkman et al., 2011; Nutbeam, 2008).

HN was associated with prompt treatment-seeking behaviours, with better numeracy corresponding to increased probability of seeking timely care. This finding aligns with research showing that individuals with higher numeracy are more likely to seek prompt care when experiencing symptoms (CDC, n.d.). Numeracy may enhance treatment-seeking through several mechanisms. First, individuals with stronger numerical skills may be better equipped to monitor symptom progression and severity, recognise patterns that indicate worsening illness, and calculate the time elapsed since symptom onset. Second, numeracy encompasses the ability to understand and apply quantitative health information, including dosing schedules and timing of medication administration (Rothman et al., 2008), which may translate into greater appreciation for the importance of early intervention. Third, numeracy influences patient activation and question-asking behaviours during medical encounters (Katz et al., 2007), suggesting that numeracy may empower individuals to navigate healthcare systems more effectively.

There are no statistically significant associations between personal and family treatment-seeking behaviour and HL. This differential effect suggests that the cognitive skills required for treatment-seeking decisions could be more closely aligned with numeracy than literacy competencies. Treatment-seeking involves assessing quantitative health risks, such as evaluating fever severity, interpreting symptom duration, and judging the urgency of medical attention based on observable changes in health status. Individuals with higher numeracy are better equipped to process this quantitative health information, estimate risk thresholds, and make timely decisions about when symptoms warrant professional care (Garcia-Retamero et al., 2019; Rolison et al., 2020). In contrast, literacy skills, which primarily involve comprehension of written health information, may be less directly applicable to the real-time, context-dependent judgements required for treatment-seeking. This finding aligns with evidence from other health domains showing that numeracy uniquely predicts risk perception and health decision-making beyond the effects of general literacy.

The absence of a literacy effect on treatment-seeking could also suggest that, in this context, where treatment decisions must often be made rapidly based on symptom observation rather than consultation of written materials, the ability to quantify and assess numerical health information plays a more critical role than text comprehension.

Higher HN was associated with lower engagement in indoor spraying. This likely reflects contextual factors. In Gabon, primary vector control strategies rely on long-lasting insecticide-treated nets and IRS (Sima-Biyang et al., 2024). IRS was reportedly practised by over 50 per cent of respondents in a study conducted in Akanda, Gabon (Pamba et al., 2021). High community-level IRS coverage may explain the observed negative relationship between HN and IRS use. Participation in IRS often follows routine public health programs rather than individual decision-making, limiting numeracy's influence on household choices (Magaço et al., 2019; Suuron et al., 2020). Individuals with higher numeracy may focus on prevention measures they can directly control, such as treatment-seeking, which could reduce their reliance on IRS. Consequently, widespread IRS coverage at the community level may weaken or invert the association between numeracy and IRS participation. The associations between HN and malaria-related behaviours remained unchanged after adjustment for education level, indicating that numeracy effects are independent of educational attainment. These findings support the notion that interventions to improve malaria-related behaviours should consider enhancing HN skills directly, rather than focusing solely on general education.

Our study had potential limitations. First, while in some areas, systematic probability sampling was used, Lambaréné utilised stratified convenience sampling with neighbourhood quotas, potentially limiting generalisability. Second, the cross-sectional design precludes causal inference; observed associations may reflect bidirectional relationships in which healthcare engagement enhances HL and HN, rather than HN and HL linking to behaviours. Third, self-reported behaviours may be subject to social desirability bias, though private interviews with trained staff mitigated this concern. Fourth, unmeasured confounding from factors such as healthcare trust, household decision-making dynamics, or cultural beliefs remains possible despite controlling for demographic and health system characteristics. The dichotomised HL scale exhibited a ceiling effect (25.6% at maximum), limiting precision at high literacy levels, an inherent limitation of the HLS-EU-Q16 analytical framework (Rouquette et al., 2018). However, for examining literacy's role in malaria prevention, the dichotomised scale was adequate given strong psychometric properties (reliability, known-groups discrimination, IRT model fit). Only 0.4 per cent achieved the maximum score on the original four-point scale, suggesting researchers requiring discrimination across the full literacy spectrum could retain the original format. Despite these limitations, the study's strengths include adequate statistical power from a large sample size, use of internationally validated and locally adapted HL and HN instruments, and geographic diversity across urban and rural settings. Future research should use longitudinal designs and examine additional health outcomes and behaviours, including vaccination behaviours.

C.3.6 Robustness Checks

To ensure the validity of our findings, we tested the robustness of our results using alternative model specifications. The results confirm that our main conclusions hold across different estimation frameworks and measurement approaches in Tables C.18 and C.19. First, we employed a mediation framework to test whether dosing knowledge and asking questions mediated the relationships between HL, HN, and health behaviours. Contemporary mediation analysis (O'Rourke et al., 2018; Rucker et al., 2011) recognises that mediation can occur even in the absence of a significant total effect, representing patterns in which HN and HL affect the behaviours entirely through the mediator (indirect-only mediation). Therefore, variables which showed no direct association with HL or HN were included in mediation analyses to test whether HL or HN affects these behaviours through mediators. We estimated our models by utilising dosing knowledge and asking questions as mediators in the relationships between HN, HL, and malaria-control behaviours.

The results of the mediation analysis are shown in Tables C.18 and C.19 as models 1 and 2. Asking health practitioners questions and knowledge of dosing significantly mediated the relationship between HL and malaria-related behaviours. Complete mediation was observed for treatment-seeking behaviours (both self and family) through both pathways and for bednet use through only asking questions. For treatment adherence, HL showed partial mediation through both asking questions and dosing knowledge. HN demonstrated mixed mediation patterns. While it influenced treatment adherence entirely through asking questions, effects on treatment-seeking behaviours operated through both direct pathways and indirect pathways (though indirect effects were not always statistically significant), indicating that numeracy influences treatment-seeking behaviour through multiple mechanisms. Dosing knowledge did not mediate any HN effects.

These findings show that HL and HN both support malaria prevention behaviours, but operate through distinct mechanisms: HL operates through enabling mechanisms that enhance communication to influence behaviours, whereas HN influences behaviour through both asking questions as an enabling mechanism and direct effects independent of this mediation. Our core findings remain robust with significant total effects. Overall, the results indicate that enhancing HL and HN can improve malaria-related behaviours, particularly when individuals are encouraged to engage actively with healthcare providers. Including community fixed effects into our model to control for unobserved heterogeneity and account for variation across communities did not alter our findings, and our conclusions remained valid as seen in model 3 in Tables C.18 and C.19.

C.4 Conclusion

This study makes two important contributions. First, it provides validated, culturally adapted instruments for assessing HL and HN in Gabon. The HL scale, as measured by the HLS-EU-Q16, demonstrated adequate psychometric properties. The HN scale similarly showed acceptable psychometric properties and meaningfully differentiated between population groups based on education level, residence, age, and health literacy. These validated instruments can support future HL and HN assessments and enable evaluation of health promotion programmes in similar settings.

Then, our study provides empirical evidence that HN and HL are independently associated with malaria-related behaviours, even after accounting for educational level and other demographic and socioeconomic factors. HL primarily supports dosing knowledge, while HN facilitates prompt treatment-seeking decisions. Both are necessary for treatment adherence and engagement with medical practitioners. The findings extend previous research on HN and HL, predominantly conducted in high-income settings, to the context of infectious disease prevention and control in endemic areas. Effective malaria interventions must address the potential of both HL and HN through tailored strategies, while recognising that structural determinants, including education, socioeconomic status, and healthcare access, remain fundamental drivers of health behaviours. By understanding when literacy matters, when numeracy matters, and when structural factors predominate, programmes can strategically allocate resources to support malaria prevention and treatment behaviours in the most effective way in endemic populations. The validated measures provide tools for future research and programme evaluation.

C.5 References

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C.6 Appendix

Table C.12: DIF Analysis of the Health Literacy Scale

Item	Logistic Regression			Mantel-Haenszel		
	1	2	3	1	2	3
1. Find information on treatments of illnesses that concern you?	N	N	N	N	N	N
2. Find out where to get professional help when you are ill?	N	*	N	N	*	N
3. Understand what your doctor says to you?	N	N	N	N	N	N
4. Understand your doctor's or pharmacist's instructions on how to take a prescribed medicine?	N	N	N	N	N	N
5. Judge when you may need to get a second opinion from another doctor?	*	N	N	N	N	N
6. Use information the doctor gives you to make decisions about your illness?	N	N	N	N	N	N
7. Follow instructions from your doctor or pharmacist?	N	N	N	N	N	N
8. Find information on how to manage mental health problems like stress or depression?	N	N	N	N	N	N
9. Understand health warnings about behaviour such as smoking, low physical activity and drinking too much?	N	N	N	*	N	*
10. Understand why you need health screenings?	N	N	*	N	N	N
11. Judge if the information on health risks in the media is reliable?	N	N	N	*	N	N
12. Decide how you can protect yourself from illness based on information in the media?	N	N	N	N	N	*
13. Find out about activities that are good for your mental well-being?	N	*	N	N	N	N
14. Understand advice on health from family members or friends?	*	N	N	*	N	N
15. Understand information in the media on how to get healthier?	N	N	N	*	N	N
16. Judge which everyday behaviour is related to your health?	N	*	N	N	N	*

Note: 1-Education; 2-Sex; 3-Age group: N-No significant DIF detected; *= Significant DIF detected

Table C.13: Variations in Health Behaviours by Health Literacy (Ordinal Outcomes)

Malaria Behaviour	Chi^2 p-value[a]	k-wallis[b] (HL score)
Bednet use	p= 0.934	p=0.773
Prompt treatment-seeking (self)	p= 0.310	p=0.049**
Medication adherence	p=0.032**	p=0.052*
Prompt treatment-seeking (family)	p= 0.571	p=0.219
Asking questions	P<0.001***	p=0.005**

Notes: Behaviours measured on a 5-point scale (0=never to 4=always). [a]Chi-square tests association between categorical HL levels (inadequate/ problematic/ sufficient) and ordinal behaviour responses. [b]Kruskal-Wallis tests association between continuous HL score (0-16) and ordinal behaviour responses. ***, **, * significant at 1%, 5%, and 10% level respectively.

Table C.14: Variations in Health Behaviours by Health Numeracy (Ordinal Outcomes)

Malaria Behaviour	ANOVA (F, p-value)
Bednet use	9.88, p=0.000***
Prompt treatment-seeking (self)	14.89, p=0.000***
Medication adherence	9.65, p=0.000***
Prompt treatment-seeking (family)	13.84, p=0.000***
Asking questions	10.84, p=0.000***

Notes: Analysis based on the total score calculated as a sum across all items (0 to 10). ***, **, * significant at the 1, 5, and 10%-level respectively.

Table C.15: Binary Logistic Regression for Categorised Health Literacy

	OR [95% CI]		
Malaria Behaviour	Unadjusted OR	Adjusted OR[a]	Adjusted OR[b] (
Prompt treatment-seeking (self)			
Problematic HL	0.328*** [0.178,0.607]	0.539 [0.223,1.308]	0.526 [0.213,1.301]
Sufficient HL	0.694 [0.400,1.203]	0.968 [0.432,2.167]	0.928 [0.402,2.139]
Dosing knowledge			
Problematic HL	1.570 [0.892,2.763]	1.862* [0.992,3.491]	1.818* [0.966,3.421]
Sufficient HL	2.659*** [1.623,4.357]	3.021*** [1.759,5.186]	2.887*** [1.665,5.006]
Indoor spraying			
Problematic HL	4.253*** [2.294,7.886]	3.403*** [1.596,7.257]	3.423*** [1.594,7.352]
Sufficient HL	2.089*** [1.211,3.605]	2.003** [1.010,3.973]	1.991* [0.986,4.019]
Medication adherence			
Problematic HL	0.504* [0.245,1.039]	1.009 [0.434,2.350]	0.997 [0.415,2.394]
Sufficient HL	1.372 [0.688,2.737]	2.365** [1.071,5.224]	2.339** [1.005,5.444]
Prompt treatment-seeking (Family)			
Problematic HL	0.427*** [0.234,0.780]	0.690 [0.316,1.508]	0.681 [0.309,1.498]
Sufficient HL	0.936 [0.545,1.609]	1.259 [0.611,2.594]	1.217 [0.580,2.553]
Asking questions			
Problematic HL	1.540 [0.859,2.761]	1.883* [0.917,3.864]	1.751 [0.841,3.651]
Sufficient HL	3.388*** [2.005,5.726]	3.825*** [2.008,7.286]	3.417*** [1.737,6.719]

Notes: ***, **, * significant at the 1, 5, and 10%-level, respectively. [a]Coefficients adjusted for age, sex, residence, employment, recent malaria exposure, insurance status, proximity to health centres, source of health information, and availability of community health resources (including malaria prevention programs). [b]additionally adjusts for education level. All models were estimated using robust standard errors. OR= Odds Ratios, CI = Confidence interval. Analysis based on binary measures of the malaria behaviours. Inadequate HL is the base category in the regression.

Table C.16: Ordered Logistic Regression for Health Literacy

Malaria Behaviour	Health Literacy		
	Unadjusted OR (95% CI)	Adjusted OR[a] (95% CI)	Adjusted OR[b] (95% CI)
Prompt treatment-seeking (self)	1.006 [0.976,1.038]	1.011 [0.977,1.048]	1.012 [0.975,1.052]
Medication adherence	1.067*** [1.028,1.106]	1.083*** [1.039,1.129]	1.089*** [1.043,1.137]
Prompt treatment-seeking (family)	1.017 [0.985,1.052]	1.026 [0.988,1.065]	1.031 [0.992,1.072]
Asking questions	1.119*** [1.072,1.167]	1.101*** [1.054,1.151]	1.092*** [1.046,1.141]

Notes: ***, **, * significant at the 1, 5, and 10%-level respectively. [a]Coefficients adjusted for age, sex, residence, employment, recent malaria exposure, insurance status, proximity to health centres, source of health information, and availability of community health resources (including malaria prevention programs). [b]additionally adjusts for education level. All models were estimated using robust standard errors. OR= Odds Ratios, CI = Confidence interval. Analysis based on ordinal measurement (Always/Often /Sometimes/ Rarely/ Never).

Table C.17: Ordered Logistic Regression for Health Numeracy

Malaria Behaviour	Health Numeracy		
	Unadjusted OR (95% CI)	Adjusted OR[a] (95% CI)	Adjusted OR[b] (95% CI)
Prompt treatment-seeking (self)	1.090*** [1.030,1.154]	1.096*** [1.029,1.168]	1.092*** [1.022,1.166]
Indoor spraying	0.799*** [0.747,0.854]	0.776*** [0.721,0.835	0.762*** [0.705,0.825]
Treatment Adherence	0.922*** [0.868,0.978]	0.917*** [0.859,0.979]	0.910***[0.853,0.972]
Prompt treatment-seeking (family)	1.049* [0.992,1.109]	1.054* [0.990,1.121]	1.057* [0.991,1.129]
Asking questions	1.008 [0.953,1.068]	0.996 [0.932,1.064]	0.971 [0.905,1.042]

Notes: ***, **, * significant at the 1, 5, and 10%-level respectively. Coefficients estimated using robust standard errors. [a]adjusted for age, sex, residence, employment, proximity to health centres and source of health information and recent malaria exposure. [b]education level included. OR= Odds Ratios, CI = Confidence interval. Analysis based on ordinal measurement (Always/Often /Sometimes/ Rarely/ Never).

C.6.1 Robustness Checks

Table C.18: Robustness Check: Mediation Analysis - Health Numeracy

	Model 1 [95% CI]			Model 2 [95% CI]			Model 3
Malaria Behaviour	TE	DE	IE	TE	DE	IE	AME [95% CI]
Prompt treatment-seeking (self)	0.17** [0.04, 0.30]	0.08** [0.001, 0.17]	0.09 [-0.02, 0.18]	0.06 [-0.05, 0.18]	0.11*** [0.03, 0.20]	-0.05 [-0.12, 0.03]	0.02** [0.002,0.03]
Indoor spraying	-0.15*** [-0.23, -0.06]	-0.18*** [-0.26, -0.09]	0.03 [-0.02, 0.08]	-0.19*** [-0.27,-0.10]	-0.17*** [-0.25,-0.09]	-0.02 [-0.05, 0.01]	-0.03*** [-0.05,0.02]
Treatment Adherence	0.21** [0.02, 0.41]	0.06 [-0.03, 0.16]	0.15* [0.02, 0.331]	0.04 [-0.07, 0.17]	0.09** [0.01, 0.19]	-0.05 [-0.13, 0.03]	0.01 [-0.003,0.02]
Prompt treatment-seeking (family)	0.16** [0.02, 0.30]	0.07 [-0.02, 0.15]	0.09* [-0.02, 0.21]	0.06 [-0.04, 0.15]	0.09** [0.01, 0.17]	-0.03 [-0.09, 0.02]	0.02** [0.001,0.03]
Dosing Knowledge	-0.01 [-0.11, 0.10]	-0.06 [-0.14, 0.01]	0.06 [-0.01, 0.13]				0.01 [-0.004,0.02]
Bush clearing	-0.03 [-0.17, 0.05]	-0.06 [-0.17, 0.05]	0.03 [-0.03, 0.08]	-0.06 [-0.17, 0.05]	-0.05 [-0.16, 0.06]	-0.01 [-0.04, 0.02]	
Bednet use	0.02 [-0.09, 0.13]	-0.04 [-0.12, 0.03]	0.06 [-0.02, 0.15]	-0.04 [-0.12, 0.04]	-0.03 [-0.11, 0.05]	-0.01 [-0.03, 0.01]	
Asking questions				0.05 [-0.05, 0.16]	0.09** [0.01, 0.18]	-0.04 [-0.09, 0.02]	0.01 [-0.003,0.03]

Notes: Estimates are presented as coefficients (95% confidence interval) unless otherwise indicated. ***, **, * significant at the 1, 5, and 10%-level respectively. CI = Confidence interval; AME = Average Marginal Effects. Model 1 is the mediation model using asking questions. Model 2 is the mediation model using dosage knowledge. All models were adjusted for age, sex, residence, employment, proximity to health centres, and source of health information, and estimated using robust standard errors. TE Total effect estimates, DE Direct effect, IE Indirect effect. Model 3 includes community fixed effects.

Table C.19: Robustness Check: Mediation Analysis - Health Literacy

	Model 1 [95% CI]			Model 2 [95% CI]			Model 3
Malaria Behaviour	TE	DE	IE	TE	DE	IE	AME [95% CI]
Prompt treatment-seeking (self)	0.14** [0.03, 0.25]	0.001 [-0.06, 0.06]	0.14*** [0.05, 0.23]	0.11** [0.02, 0.20]	0.0004 [-0.06, 0.06]	0.11*** [0.04, 0.18]	0.004 [-0.01,0.02]
Dosing Knowledge	0.16*** [0.08, 0.23]	0.10*** [0.05, 0.15]	0.06* [-0.004, 0.12]				0.02*** [0.01,0.03]
Treatment Adherence	0.30*** [0.15, 0.44]	0.08** [0.01, 0.15]	0.22*** [0.09, 0.35]	0.18*** [0.10, 0.27]	0.09*** [0.03, 0.16]	0.09** [0.02, 0.17]	0.01*** [0.01,0.02]
Prompt treatment-seeking (family)	0.17** [0.05, 0.27]	0.02 [-0.04, 0.07]	0.15*** [0.06, 0.24]	0.10*** [0.03, 0.18]	0.03 [-0.03, 0.09]	0.07** [0.02, 0.13]	0.01 [-0.003,0.02]
Indoor Spraying	0.06 [-0.02, 0.13]	0.03 [-0.03, 0.08]	0.03 [-0.03, 0.09]	0.06* [-0.00,-0.13]	0.03 [-0.02,0.08]	0.03 [-0.02, 0.09]	0.01 [-0.004,0.02]
Bush clearing	0.08 [-0.02, 0.18]	0.04 [-0.03, 0.12]	0.04 [-0.04, 0.11]	0.08* [-0.004,0.17]	0.05 [-0.03, 0.13]	0.03 [-0.03, 0.10]	
Bednet use	0.13*** [0.05, 0.21]	0.04 [-0.01, 0.09]	0.09** [0.02, 0.16]	0.06** [0.01, 0.12]	0.05** [0.002,0.10]	0.01 [-0.03, 0.06]	
Asking questions				0.16*** [0.09, 0.24]	0.11*** [0.05, 0.17]	0.05* [-0.00, 0.11]	0.02*** [0.01,0.03]

Notes: Estimates are presented as coefficients (95% confidence interval) unless otherwise indicated. ***, **, * significant at the 1, 5, and 10%-level respectively. CI = Confidence interval; AME = Average Marginal Effects. Model 1 is the mediation model using asking questions. Model 2 is the mediation model using dosage knowledge. All models were adjusted for age, sex, residence, employment, recent malaria exposure, insurance status, proximity to health centres, availability of community health resources, and source of health information, and estimated using robust standard errors. TE Total effect estimates, DE Direct effect, IE Indirect effect. Model 3 includes community fixed effects.

Figure C.2: Distribution of Health Literacy

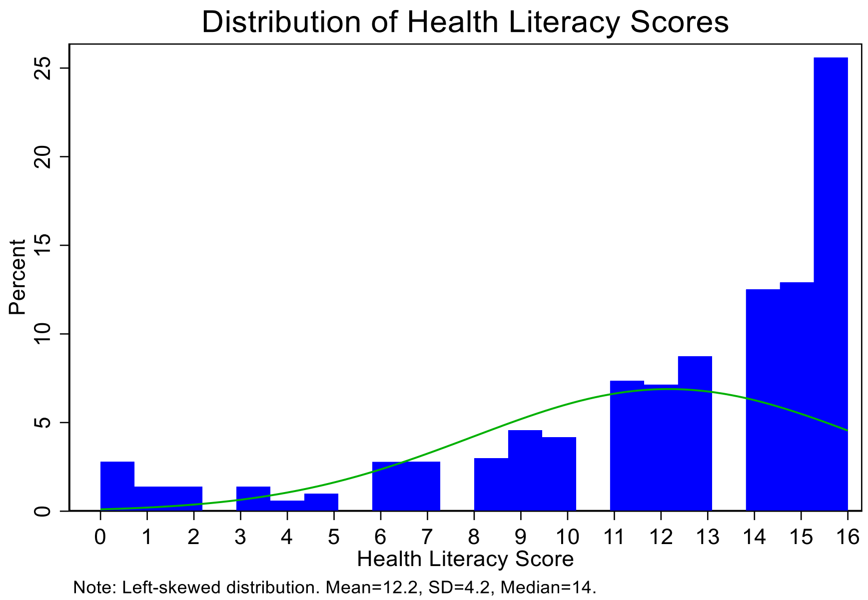


Figure C.3: Scree Plot after Factor Analysis of the Health Literacy Scale

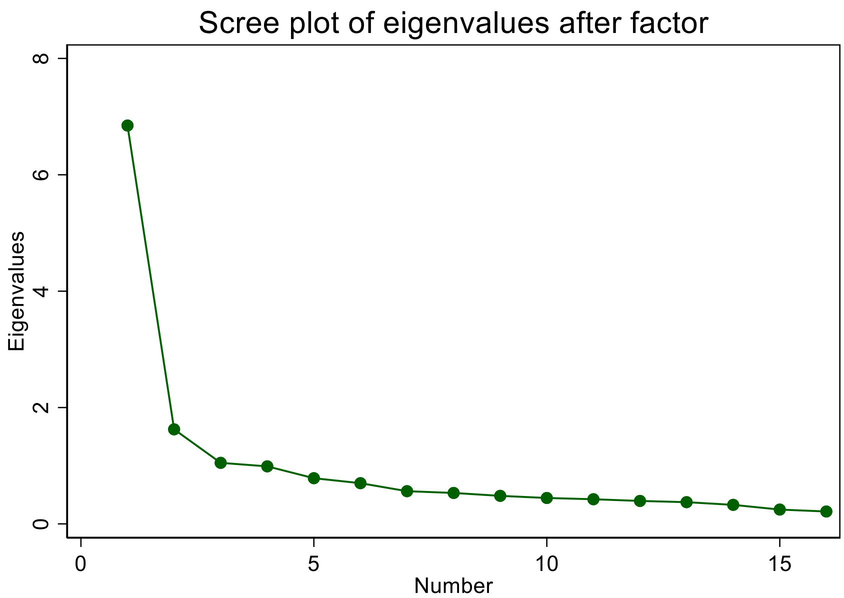
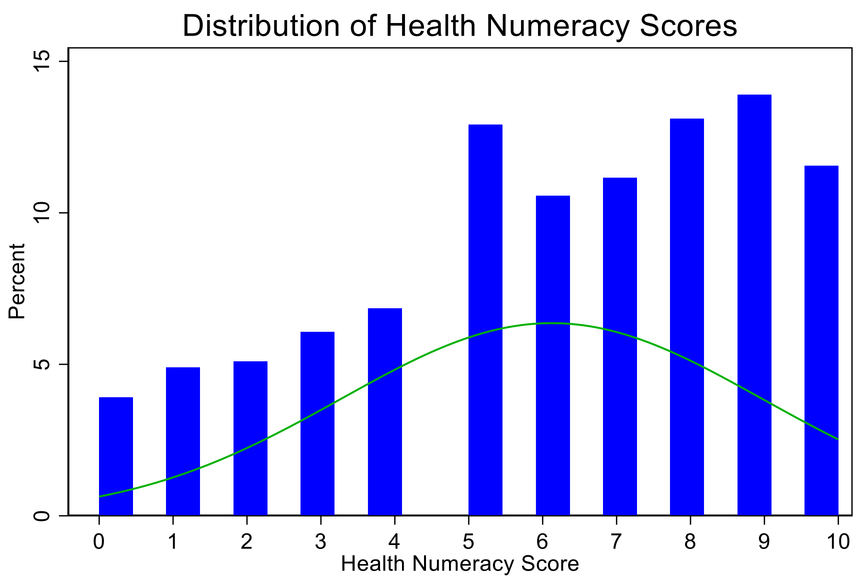


Table C.20: Factor Loadings

Item	**Factor 1**	**Factor 2**
1	0.59	-0.33
2	0.66	-0.38
3	0.75	-0.42
4	0.79	-0.33
5	0.69	-0.27
6	0.75	-0.24
7	0.75	-0.29
8	0.50	0.28
9	0.68	0.11
10	0.60	0.40
11	0.71	0.34
12	0.76	0.30
13	0.73	0.28
14	0.64	0.30
15	0.78	0.18
16	0.69	0.20
Eigenvalue	7.77	1.46
Variance Proportion	0.49	0.09

Figure C.4: Distribution of Health Numeracy



Note: Mean=6.12, SD=2.9, Median=6

C.6.2 Questionnaire

Record ID ______________________

Site: Lambaréné ☐ Four-place ☐ Sindara ☐ Other ☐

Date: ___/___/______

Is the household part of demographic surveillance? Yes ☐ No ☐

If yes, Household number___________________________________

Section A: Demographic Information

A1. Do you know your date of birth? Yes☐ No ☐

A2: If Yes in A1, Date of birth ___/___/______ ; If No, please state Age

A3. Sex: Male☐ Female ☐

A4. Education Level: None☐ Primary ☐ Secondary ☐ Tertiary ☐

A5. Marital Status: Single ☐ Married ☐ Divorced ☐ Widowed ☐ Cohabitation ☐

A6. Number of people currently living in your household including you: __________

A6. Number of people

a) Under the age of 5 _______

b) Above the age of 5 _______

A7. Area of residence Rural ☐ Urban ☐

Section B: Economic Factors

B1. Employment Status: Employed ☐ Unemployed ☐ Self-employed ☐ Retired ☐

B2. Occupation: ____________________________

B3. Health Insurance Status: Insured ☐ Uninsured ☐

B4. If Insured, covered by: Public health insurance (CNAMGS) ☐ Private Health Insurance ☐ Others ☐ Specify____

Section C: Health Environment

C1. Availability of Health Services (e.g., clinics, hospitals) in your area: Yes ☐ No ☐

C2. Closeness of the nearest health facility to your residence

Less than 1km ☐ 1km to 3kms ☐ 3kms to 5kms ☐ More than 5kms☐

C3. Community Health Resources (e.g., malaria prevention programs): Available ☐ Unavailable ☐

Section D: Malaria Knowledge

D1. Have you or any member of your family had a malaria experience or exposure in the past 2 weeks?

Yes ☐ No ☐ Not sure ☐

D2. Malaria is primarily transmitted by

Mosquito bites ☐ Contaminated water ☐ Person-to-person contact ☐

Other (please specify): ________________________ No Idea ☐

D3. The preventive measures for avoiding malaria are (Select all that apply)

Sleeping under bed nets ☐ Using insect repellent/insecticide ☐ Taking anti-malarial medication ☐ Eliminating mosquito breeding sites ☐ Other (please specify): ______________________________

D4. What are the most common symptoms of malaria? please select all that apply.

Fever ☐ Headaches ☐ Muscle pain ☐ Fatigue ☐ Lack of appetite ☐ Diarrhea ☐ Other ____

D5. Information about malaria and its prevention/treatment is usually sourced from (Select all that apply)

Health centres/clinics ☐ Media (TV, radio, Phone) ☐ Community health workers ☐

Friends and family ☐ Other (please specify): ____

Section E: Health Literacy

Indicate, on a scale from very easy to very difficult, how easy it is for you to...

Health Literacy	very easy	easy	difficult	very difficult
... find information about malaria/disease treatments that affect you?	☐	☐	☐	☐
... know where to get professional help when you are sick? (e.g. doctor, nurse, pharmacist or psychologist)	☐	☐	☐	☐
... understand what a doctor is telling you?	☐	☐	☐	☐
... understand your doctor's or pharmacist's instructions on how to take your medication?	☐	☐	☐	☐
... know when it would be useful to have the opinion of another doctor?	☐	☐	☐	☐
... use the information the doctor gives you to make decisions about your disease or illness?	☐	☐	☐	☐
... follow the instructions of your doctor or pharmacist?	☐	☐	☐	☐
... find information on what to do in case of psychological problems? (e.g. stress, depression or anxiety)	☐	☐	☐	☐
... understand the warnings about the health impact of certain behaviours such as smoking, not exercising enough, and drinking too much?	☐	☐	☐	☐
... understand the information on recommended screenings and examinations? (e.g., cancer screening, blood sugar test)	☐	☐	☐	☐
... assess the reliability of information available in the media about what is dangerous to health? (e.g. newspapers, television or internet)	☐	☐	☐	☐
... know how to protect yourself from diseases from the information available in the media? (e.g. newspapers, television or internet)	☐	☐	☐	☐
... find out about activities that are beneficial to your health and well-being? (e.g. exercise, football, running)	☐	☐	☐	☐
... understand the health advice of your family or friends?	☐	☐	☐	☐

... understand the information available in the media to be healthier?	☐	☐	☐	☐
... identify what behaviours in your everyday life have an impact on your health?	☐	☐	☐	☐

Section F: Subjective Numeracy

For each of the following questions, please check the box that best reflects how good you are at doing the following things:

F1. How good are you at working with fractions? in everyday tasks, such as dividing food, measuring ingredients, or sharing money?

❑1 ❑2 ❑3 ❑4 ❑5 ❑6

Not at all good Extremely good

F2. How good are you at working with percentages? like calculating discounts, price increases?

❑1 ❑2 ❑3 ❑4 ❑5 ❑6

Not at all good Extremely good

F3. How good are you at calculating a 15% increase in the price of food?

❑1 ❑2 ❑3 ❑4 ❑5 ❑6

Not at all good Extremely good

F4. How good are you at figuring out how much an item like electronics or food will cost if it has a discount of 25%?

❑1 ❑2 ❑3 ❑4 ❑5 ❑6

Not at all good Extremely good

For each of the following questions, please check the box that best reflects your answer:

F5. When reading the newspaper or watching TV or using the phone, how helpful do you find tables and graphs that are parts of a story?

❑1 ❑2 ❑3 ❑4 ❑5 ❑6

Not at all helpful Extremely helpful

F6. When people tell you the chance of something happening, do you prefer that they use words (“it rarely happens”) or numbers (“there’s a 1% chance”)?

❑1 ❑2 ❑3 ❑4 ❑5 ❑6

Always Prefer Words Always Prefer Numbers

F7. When you hear a weather forecast in Gabon, do you prefer predictions using percentages (e.g., “there will be a 20% chance of rain today”) or predictions using only words (e.g., “there is a small chance of rain today”)?

❑1 ❑2 ❑3 ❑4 ❑5 ❑6

Always Prefer Percentages Always Prefer Words

F8. How often do you find numerical information to be useful?

❑1	❑2	❑3	❑4	❑5	❑6
Never					Very Often

Section G : Health Numeracy

Choose the right option

G1. Jean has diabetes. His goal is to have his blood sugar between 80 and 150 in the morning. Which of the following blood sugar readings is within his goal?

55 ☐ 140 ☐ 165 ☐ 180 ☐

G2. David has a headache from fever with a pain rating of 5 on a pain scale of 1 (no pain) to 10 (worst possible pain). One day later, after taking malaria medicine David still has pain but it is better. Now, what pain rating might David give?

3 ☐ 5 ☐ 7 ☐ 9 ☐

G3. Loic has high blood pressure (hypertension). The doctor explained that people with higher blood pressure have a greater chance of having a stroke. The doctor showed Loic different risk levels. Which risk level has the highest chance of stroke?

33% ☐ 50% ☐ 75% ☐ 98% ☐

G4. A medical study will randomly assign people so that people are equally likely to get malaria medicine A or medicine B. If there are 300 people in the study, about how many are expected to get medicine A?

100 people ☐ 150 people ☐ 200 people ☐ 250 people ☐

G5. The rapid diagnostic test (RDT) for malaria detects the presence of malaria parasites in the blood. However, the test sometimes gives false positive results, so about 30% of people with a positive test do not actually have malaria. Marion had a positive malaria test. What is the chance that Marion truly has malaria?

0% ☐ 30% ☐ 70% ☐ 100% ☐

G6. A study found a new diabetes medicine decreased the risk of complications by about 30%. The study was 95% sure that the real benefit was between 10% and 50%. Which of the following is <u>not</u> in the expected range of benefit?

11% decrease ☐ 30% decrease ☐ 45% decrease ☐ 95% decrease

G7. Ali had a fever. The doctor told him to come to the hospital if his temperature was above 38^0C. Otherwise, John should take Paracetamol and rest. If Ali's temperature is as shown in the picture below, what should John do?

Take Paracetamol and rest ☐ Go to the hospital ☐

G8. A nutrition label for Cassava Flour is shown below. How many calories did Ange eat if she had 2 cups of food?

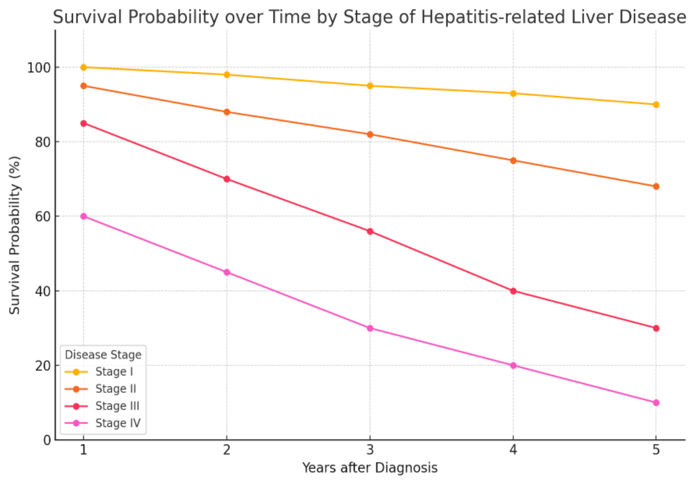
140 calories ☐ 280 calories ☐ 560 calories ☐ 680 calories ☐

Nutrition Facts Serving Size 1 cup (228g) Servings per Container 2	
Amount Per Serving	
Calories 280	**Calories from Fat** 120
	% Daily Value*
Total Fat 13g	20%
Saturated Fat 5g	25%
Trans Fat 2g	
Cholesterol 2mg	10%
Sodium 660 mg	28%
Total Carbohydrate 31g	10%
Dietary Fiber 3g	
Sugars 5g	
Protein 5g	
Vitamin A 4%	Vitamin C 2%
Calcium 15%	Iron 4%

* Percent Daily Values are based on a 2,000-calorie diet. Your Daily values may be higher or lower depending on your calorie needs.

G9. The graph below shows the outcomes of a group of men diagnosed with Hepatitis B. Rose has stage II Hepatitis. According to the graph, what is his chance of surviving 3 years after diagnosis?

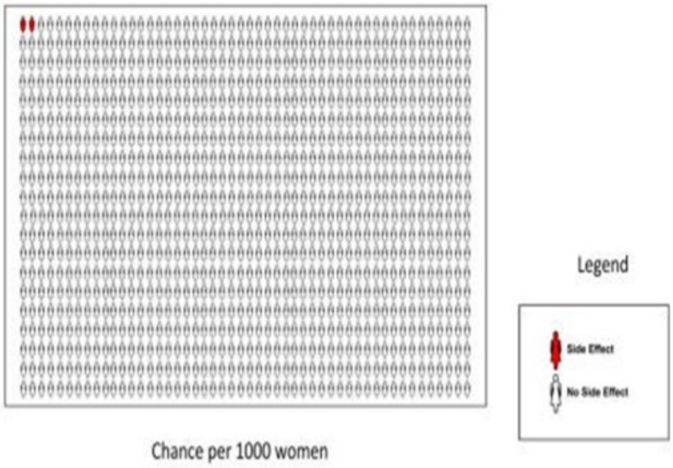
56% ☐ 82% ☐ 92% ☐ 100% ☐



Key: Stage I: Early localized disease, Stage II: Moderate progression within the liver, Stage III: Advanced local disease, Stage IV: Metastatic or severely advanced disease

G10. Rima is taking a new Antimalarial medicine. The chance of a side effect is very small as shown in the graph below. What number best shows her chance of having a side effect?

0.0002 ☐ 0.002 ☐ 0.02 ☐ 0.20 ☐



Section H: Malaria Control Behaviours

H1. How frequently do you use bed nets as a preventive measure against malaria?
Every night ☐ Most nights ☐ Occasionally ☐ Rarely ☐ Never ☐

H2. Is your house treated with indoor residual spraying (IRS) for malaria control?
Yes ☐ No ☐ Not sure ☐

H3. Are bushes around your home regularly cleared?
Yes ☐ No ☐ Not sure ☐

H4. When facing any illness (fever/cough), I go to the health centre or speak with a health practitioner or doctor immediately.
Always ☐ Often ☐ Occasionally ☐ Rarely ☐ Never ☐

H5. If anyone in my household has a fever or cough, I make sure they see a doctor or health care practitioner promptly.
Always ☐ Often ☐ Occasionally ☐ Rarely ☐ Never ☐

H6. When a doctor/ health practitioner advises that I should take medicine three times a day, I know that I should take the medicine every 8 hours.
Yes ☐ No ☐ Not sure ☐

H7. Do you complete the full course of medication when prescribed for malaria treatment or any treatment, even if symptoms disappear?
Always ☐ Often ☐ Occasionally ☐ Rarely ☐ Never ☐

H8. I ask my doctor or health care practitioner questions about health (including malaria and other illnesses).
Always ☐ Often ☐ Occasionally ☐ Rarely ☐ Never ☐

Section I: Patient Perspectives on Numerical Health Information Delivery on dosages

I1. How would you prefer to receive numerical information about medication dosages and treatment regimens? (Select all that apply)
Written instructions on medication labels ☐ Verbal explanations from healthcare providers☐ Visual aids such as dosage charts or diagrams ☐ Sent as reminders or alerts through digital/mobile platforms ☐ Other (please specify) ____

I2. When discussing numerical data related to medication dosages, which format do you find most helpful for understanding and adherence? (Select all that apply)
Milligrams or grams ☐ Dosage frequency per day ☐ Duration of treatment in days or weeks ☐ Comparisons with recommended dosages ☐ Other (please specify) ______________________________

I3. How beneficial would numerical information be for managing medication dosages effectively? (Select all that apply)
Understanding proper dosage amounts ☐ Timing of medication intake ☐ Monitoring potential side effects or interactions ☐ Calculating dosage adjustments based on weight or age ☐ Other (please specify) ________________________________

I4. How beneficial would numerical information be for managing general health? (Select all that apply)
Understanding treatment success rates ☐ Assessing potential risks and side effects ☐ Monitoring progress over time ☐ Making informed decisions about treatment options☐ Setting health-related goals ☐ Other (please specify) ________________________________

I5. When the doctor/physician provides you with numerical information about your health (such as test results, medication instructions, or treatment options), or when you consult numerical health information, how often do you find this information difficult to understand or use?
Not applicable - I rarely receive digital health information. ☐ Always - I consistently find digital health information very difficult to understand. ☐ Often - I frequently have difficulty understanding or using digital health information. ☐ Sometimes - I find about half of the digital health information difficult to understand. ☐ Rarely - I sometimes have some minor difficulties, but I usually manage well ☐ Never - I always clearly understand numerical health information. ☐

D Institutional Quality, Aid Flows, and Malaria Burden: a Geospatial Analysis of Sub-Saharan Africa[3]

Abstract

Malaria remains a major public health challenge in sub-Saharan Africa, accounting for approximately 95 per cent of global malaria deaths despite extensive interventions. Significant disparities persist in the malaria burden across countries, with some achieving remarkable progress while others experiencing persistently high transmission rates, suggesting factors beyond resource availability influence disease control effectiveness. This study examines the relationship between institutional quality, development aid flows, and malaria burden across 38 sub-Saharan African countries during 2010-2022. The analysis used malaria cases and deaths per 1,000 population as measures of malaria burden. Key explanatory variables included development assistance for health per capita, government effectiveness indices and health worker density as institutional quality indicators, alongside control variables for intervention coverage, environmental factors, and socioeconomic conditions. Data was sourced from the World Health Organisation, United Nations Development Programme, Institute for Health Metrics and Evaluation, Malaria Atlas project, Demographic and Health Surveys, and World Bank databases. Spatial econometric models, including Spatial Durbin Models, Spatial Lag of X, and Spatial Durbin Error Models, were used to account for spatial autocorrelation and cross-border transmission effects, while fixed-effects models with Driscoll-Kraay standard errors provided baseline estimates. The study found spatial clustering of malaria burden alongside an overall reduction across sub-Saharan Africa. Malaria cases and deaths demonstrated significant spatial autocorrelation annually, indicated by Moran's I statistics. Findings revealed that increased health worker density, enhanced institutional effectiveness, and higher aid levels are positively associated with the burden. These effects persisted with lagged values of health workers and government effectiveness. The geospatial analysis reveals that the malaria burden is driven more by local conditions with limited spillover effects from neighbouring countries. Findings reveal a need for localised health systems strengthening alongside targeted regional coordination.

[3] This chapter is based on an article by Namubiru (2025), published in Malaria Journal. The version included in this dissertation is identical in content, with only minor textual differences.

D.1 Introduction

Malaria is one of the most significant public health burdens facing Sub-Saharan Africa (SSA) (Bhatt et al., 2015; Snow & Gilles, 2017), with the region accounting for 95 per cent of global malaria deaths and 94 per cent of the malaria cases despite having only 17 per cent of the world's population (WHO, 2024). Ending malaria is important for sustainable development. Sustainable development goal number three focuses on ensuring healthy lives and promotion of well-being for all at all ages, with target 3.3 postulating that, by 2030, end the epidemics of AIDS, tuberculosis, malaria, and neglected tropical diseases and combat hepatitis, water-borne diseases, and other communicable diseases (United Nations General Assembly, 2015). To achieve this target, coordinated efforts at global, regional, and national levels focus on controlling and eliminating malaria. Efforts include vector control and prevention, as well as medical interventions such as funding for diagnosis, prompt and effective treatment, intermittent preventive treatment in pregnancy, vaccines, and antimalarial drugs, complemented by public health policies and health-seeking behaviours (WHO, 2023, 2024).

Significant progress has been made since 2000, with an estimated 2.2 billion cases of malaria and 12.7 million deaths averted (WHO, 2024). Between 2000 and 2015, global malaria mortality declined by 60 per cent (Vos et al., 2020). However, the rate of improvement has plateaued, raising questions about the sustainability and effectiveness of current control strategies. The malaria burden varies widely across SSA countries. Some countries have achieved remarkable progress, while others continue to face high transmission rates. Countries like Rwanda have reduced malaria incidence by 88 per cent since 2018 (Umugwaneza et al., 2025), while others, such as Nigeria and the Democratic Republic of Congo, continue to account for over one-third of global malaria cases and deaths (WHO, 2024). Institutional quality, funding, and the capacity to implement and coordinate health interventions play a critical role in determining health outcomes (Balabanova et al., 2013; Hay et al., 2009). Theoretically, North's work on institutional quality demonstrates that effective institutions reduce transaction costs, enhance predictability, and facilitate collective action, all of which are critical elements of successful disease control programmes (North, 1990).

Development assistance for health (DAH) constitutes a significant source of funding for malaria control in SSA. Investment in malaria control reached over US$50 billion between 2000 and 2022. Global funding for malaria control and elimination totalled US$4.0 billion across 90 countries in 2023, slightly lower than the US$4.1 billion in 2022 but higher than the US$3.5 billion available in 2021, with the WHO African Region receiving 75 per cent of this funding, owing to its high malaria burden (WHO, 2024). Funding effectiveness is, however, influenced by institutional and governance factors, as well as alignment issues between donor priorities and national health strategies (Biesma et al., 2009; Ooms et al., 2008; Storeng, 2014), which determine absorptive capacity, transparency, and program implementation efficiency (Lu et al., 2010). Health worker density is a critical component of health system capacity that directly affects disease burden. A sufficient and well-distributed health workforce improves access to diagnosis, treatment, and prevention services, which are fundamental to reducing disease morbidity and mortality (Macarayan et al., 2018). However, health worker availability remains unevenly distributed across SSA countries, exacerbating inequities in malaria outcomes (Alhassan & Wills, 2024).

Malaria is transmitted through the bites of female *Anopheles* mosquitoes (WHO, 2024), but the transmission process is shaped by environmental, socioeconomic, and geopolitical factors that vary across space and time. Drug and insecticide resistance, invasive vectors, conflicts, land use, climate change and disruptions to healthcare delivery spread in spatial patterns that cross national borders, requiring regional surveillance and coordinated responses (Alout et al., 2017; Fornace et al., 2021; Klepac et al., 2024; Li et al., 2024; Ranson & Lissenden, 2016; Ryan et al., 2020; Symons et al., 2025; Tatem et al., 2013). The transmission risk may be influenced by spatial spillover effects, where neighbouring conditions affect local outcomes (Benjamin-Chung et al., 2023; Wu et al., 2023). This study assesses how institutional quality, development assistance for health, and health system capacity, as measured by health worker density, influence malaria burden in SSA, accounting for both temporal variation and spatial interdependencies across countries.

D.2 Methods

D.2.1 Data and Sources

The study employed a quantitative, secondary-data longitudinal panel design covering the period 2010 to 2022 across 38 sub-Saharan African countries (see Figure D.3 and D.4 for the included countries). The outcome variables were Malaria cases and deaths scaled per 1000 population. Data was sourced from the 2024 World Malaria report (WHO, 2024). The key explanatory variables were: Health worker density (per 100000 population) sourced from (WHO, 2024) as well as the Institute for Health Metrics and Evaluation (IHME) (IHME, n.d). The measure includes physicians, nurses, and midwives but excludes community health workers due to inconsistent reporting across countries.

Development Assistance for Health (DAH) in USD per capita sourced from the IHME and cross-checked with the annual world malaria reports (WHO, 2012-2024). These values were deflated to 2022 constant US dollars using World Bank deflators and represent total health-related development assistance, including both bilateral and multilateral flows. Institutional quality was assessed using Political stability, corruption and government effectiveness indices from the World Governance Indicators (WGI) Database. Scores originally ranged from -2.5 to $+2.5$ and were rescaled to 0 to 1, with higher values indicating better outcomes. A composite institutional quality index was generated from the three indices using Principal Component Analysis (PCA). It is referred to in the text as government effectiveness. Data was confirmed suitable for factor analysis (overall Kaiser-Meyer-Olkin (KMO) = 0.6621; the KMO value for each variable exceeded 0.5; Bartlett's test of sphericity $p=0.000 < 0.05$). The component, positively correlated with all three indices, explained 77.80 per cent of the variance and had the highest eigenvalue.

Other variables included in the model were Intervention variables: Insecticide treated nets (ITN) access (%) assessed as access to insecticide-treated nets and Long lasting Insecticide treated nets, indoor residual spraying (IRS) coverage (%), Effective treatment for malaria (%) and antenatal care coverage (ANC4), defined as the proportion of women receiving four or more antenatal visits. Data were sourced from (IHME, n.d.), the Malaria Atlas Project (Malaria Atlas Project, 2024), and supplemented with Demographic and

Health Survey (DHS) reports. Environmental factors: Precipitation data in millimetres (mm) from the World Bank Climate Change Knowledge Portal (World Bank Group, n.d.). Economic and structural factors: Gross National Income per capita (GNIpc) from the United Nations Development Programme (UNDP), and urbanicity, defined as the proportion of the population residing in urban areas, from the IHME database (IHME Data | GHDx, n.d.). These variables represent established determinants of malaria transmission and burden. In cases of missing data, additional comparisons were made using DHS and country-specific DHS reports for the various years. Interpolations using country-specific linear trends were applied where necessary. The variables, their definitions, measurements and summary statistics are described in Table D.5 in the appendix.

D.2.2 Conceptual Model and Hypotheses

The study adopted a modified health production function to analyse the effect of various determinants on malaria deaths and cases across countries. The model conceptualises health outcomes as a function of both direct and indirect pathways, consistent with Grossman's (1972) health production theory. The model is stipulated as:

$$H_{it} = f(M_{it}, I_{it}, A_{it}, G_{it}, E_{it}, S_{it}) \tag{5}$$

Where H_{it} represents health outcomes (malaria cases and deaths) for country i at time t; M_{it} represents medical and non-medical interventions (health worker density, IRS coverage, ITN access, ANC4, effective treatment); I_{it} represents institutional quality (government effectiveness); A_{it} represents aid flows (DAH per capita); G_{it} represents economic conditions (GNI per capita); E_{it} represents environmental factors (precipitation); and S_{it} represents structural factors (urbanisation). This model integrates both supply-side and contextual variables, recognising that malaria outcomes result not only from health system capacity but also from broader socio-political and environmental environments.

D.2.3 Data Analysis

To analyse the data, 1) descriptive methods were applied, including summary statistics, line graphs, bar graphs, heat maps, and hotspot analysis. These visualised geographic clustering, temporal trends, and the distribution of malaria cases and deaths per 1,000 population across countries. For the regressions, both malaria outcomes (cases and deaths per 1,000) were log-transformed to address scale and skewness issues. 2) Baseline regression analysis that included pooled Ordinary Least Squares (OLS) to establish baseline relationships assuming homogeneity across countries and time periods; Panel fixed effects (FE) models to assess temporal variations in the relationships. The Panel FE model was adopted because it was supported by the Hausman test ($p < 0.05$), and, finally, one-year lag models (Wooldridge, 2010) were used to capture delayed intervention effects and any implementation delays. For this model, one-year lags were applied to all explanatory variables except precipitation and effective treatment. Diagnostic tests after the Panel FE model detected heteroskedasticity, cross-sectional dependence, and serial correlation, which were addressed using Driscoll–Kraay standard errors model with fixed effects. This technique produces standard errors robust to cross-sectional and temporal dependence (Driscoll & Kraay, 1998). Inaddition, panel regression models with Panel-Corrected standard errors and robust clustering to address panel-specific autocorrelation and heteroskedasticity were estimated. The standard errors were clustered at the country level to account for within-country correlation of observations over time while allowing for heteroskedasticity. Elasticities and marginal effects were calculated for key interventions (ITN access, IRS coverage, ANC4, health worker density, and DAH per capita) to quantify the percentage change in outcomes from a 1 percentage change in each variable.

3) Spatial panel regression models were used to assess the geospatial relationship of the variables with the malaria burden. These models were run after detecting spatial autocorrelation in the malaria burden using Global Moran's I statistics (Moran, 1948). Moran's I statistic tests the null hypothesis that the malaria outcomes in one country are independent of those observed in neighbouring countries. The index can take values in the interval -1 to 1, and a statistical significance test is based on p-values. To identify spatial clustering, Local Moran's I was applied as a local indicator of spatial association (LISA; Anselin, 1995). For each country, LISA indicates whether it forms part of a cluster (High-High or Low-Low), acts as a spatial outlier (High-Low or Low-High), or shows no significant spatial association. Spatial dependence in malaria outcomes was identified (see Table D.6 in the appendix), justifying the estimation of spatial panel models. Several spatial models were

estimated using maximum likelihood (Belotti et al., 2017), including the Spatial Durbin Model (SDM), Spatial Durbin Error Model (SDEM) and the spatial lag model of X (SLX), after yielding lower AIC and BIC values compared to the Spatial Autoregressive Model (SAR) and the spatial error model (SEM). However, the robustness checks were based on the SDM, as it had better coefficients for the Log-likelihood ratio test. The SDM incorporates both spatial lags of outcomes and explanatory variables, allowing for both spillover effects in outcomes and spatial spillovers in intervention effects. It tests whether interventions in neighbouring countries affect local outcomes, and it captures cross-border intervention spillovers. A row-standardised binary contiguity spatial weight matrix was used to estimate these models. The matrix assigns a value of 1 to country pairs sharing a border and 0 otherwise, capturing neighbouring-country relationships important for modelling policy diffusion and regional interventions.

D.3 Results

D.3.1 Descriptive Statistics

Figures D.1 and D.2 show a consistent decline in annual average malaria cases and deaths per 1000 population from 2010 to 2022 in SSA. In Figures D.3 and D.4, countries in Western Africa (Burkina Faso, Niger, Sierra Leone) have significantly higher case and death rates per 1000, while those in Southern Africa (Botswana, South Africa, Eswatini) have significantly lower rates. The hotspot analysis, conducted to identify spatial clustering in malaria outcomes, is shown in Figures D.5 and D.6. There is a distinct spatial distribution of both malaria cases and deaths. The western part of Africa has distinctively high cases and deaths on average over time, indicating a regional hotspot. This is indicated by the red High-High clusters, which show that countries with high malaria cases are surrounded by neighbours with similarly high values. High-Low outliers in pink in the south-eastern part of Africa indicate countries with high malaria burden surrounded by lower-burden neighbours, such as Mozambique, which stands out with high cases and deaths compared to the neighbours, which may reflect localised health system or ecological differences. Similar results are reported by the hotspot map, which shows a concentration of high cases and deaths in the western part of Africa and low cases and deaths in the southern part of Africa.

Figure D.1: Graph showing Annual Average Malaria Cases per 1000 (2010 to 2022)

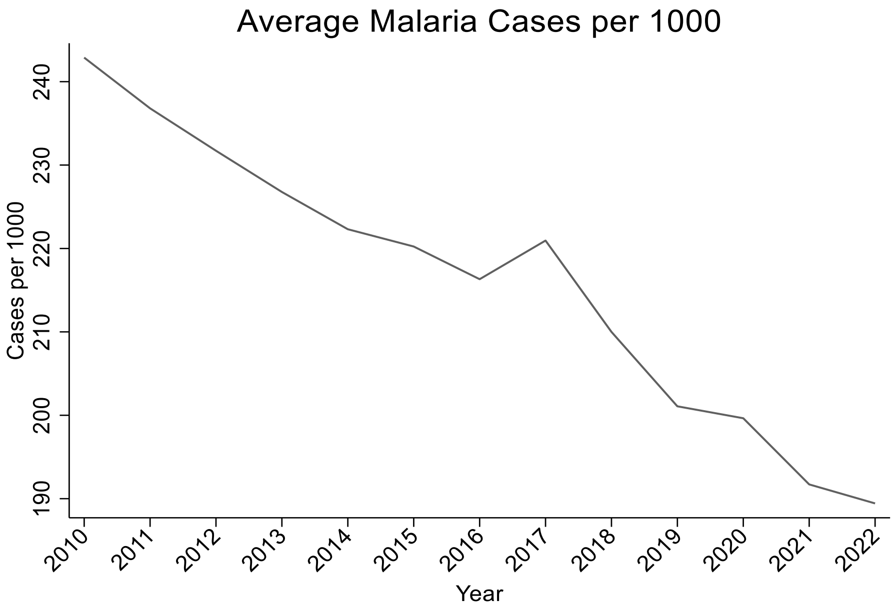


Figure D.2: Graph showing Annual Average Malaria Deaths per 1000 (2010 to 2022)

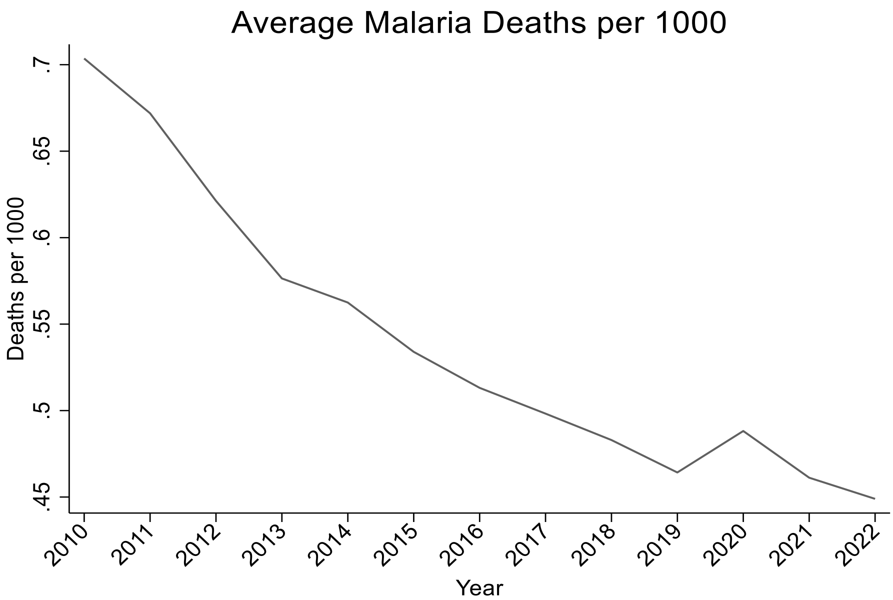


Figure D.3: Plot of Mean Malaria Cases per 1000 (2010 to 2022)

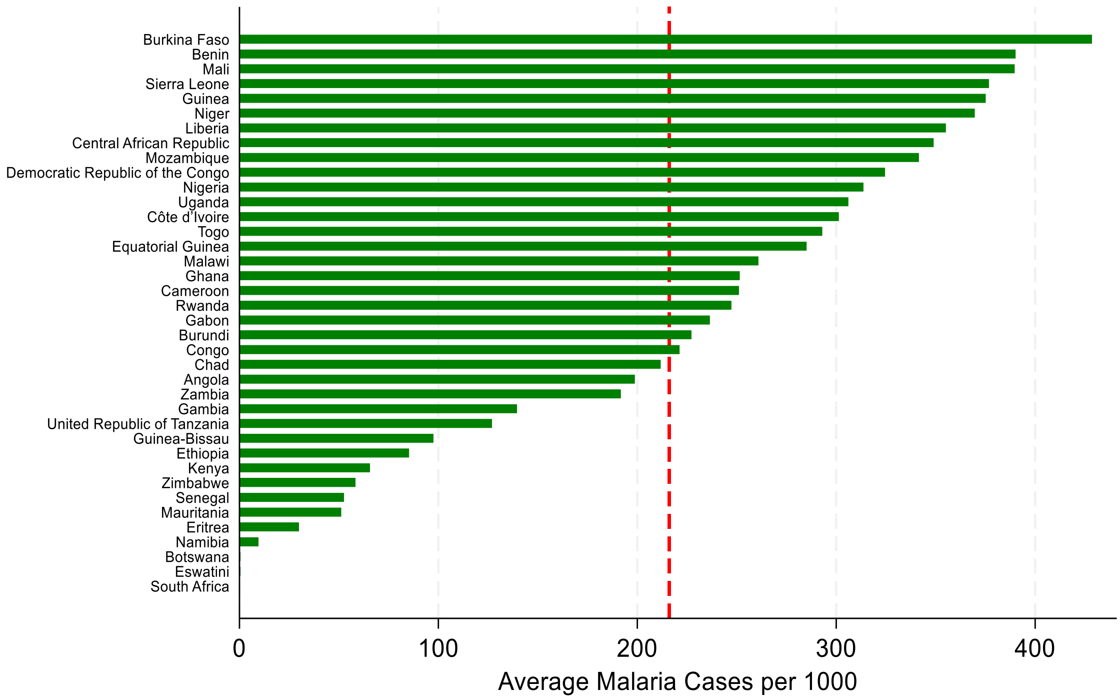


Figure D.4: Plot of Mean Malaria Deaths per 1000 (2010 to 2022)

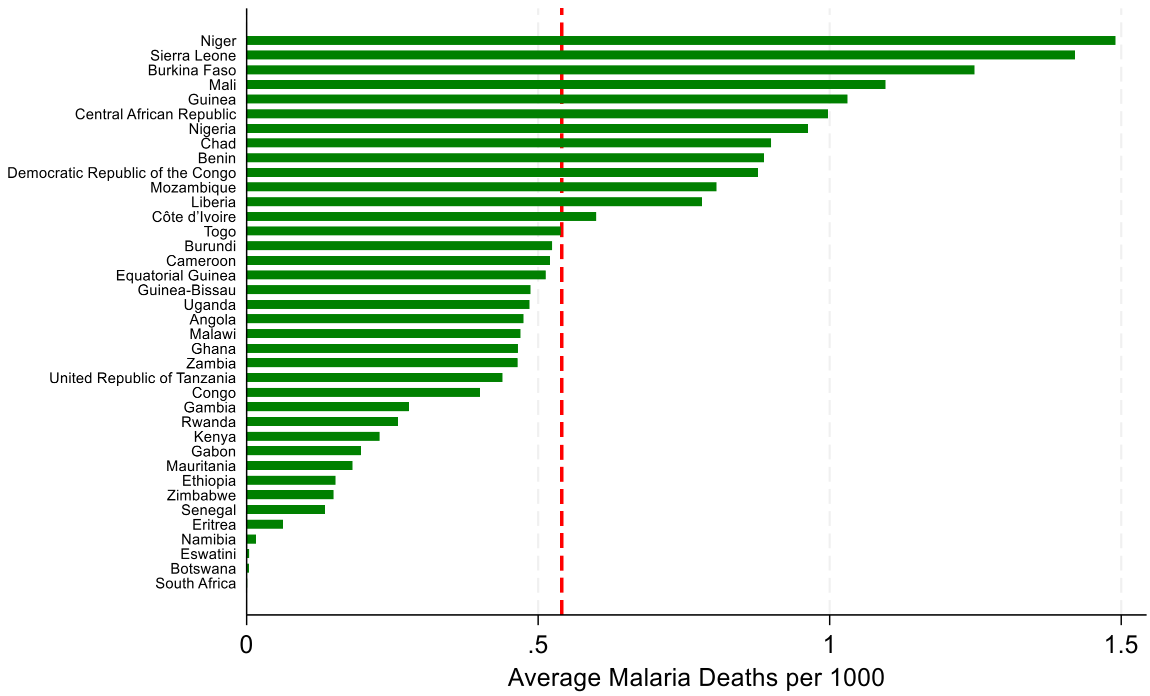


Figure D.5: Spatial Distribution and Hotspot Analysis of Malaria Cases per 1000

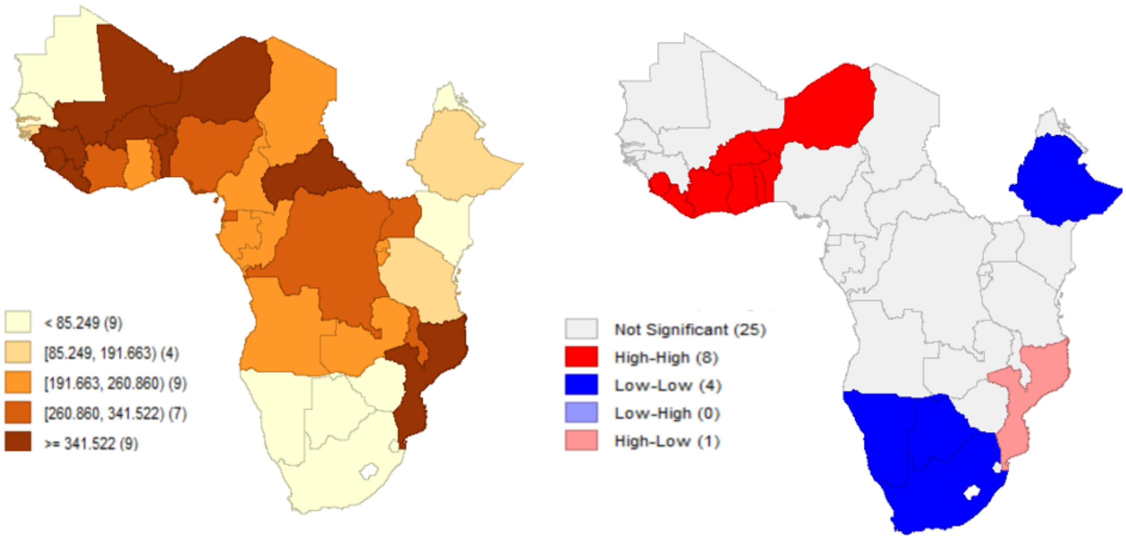
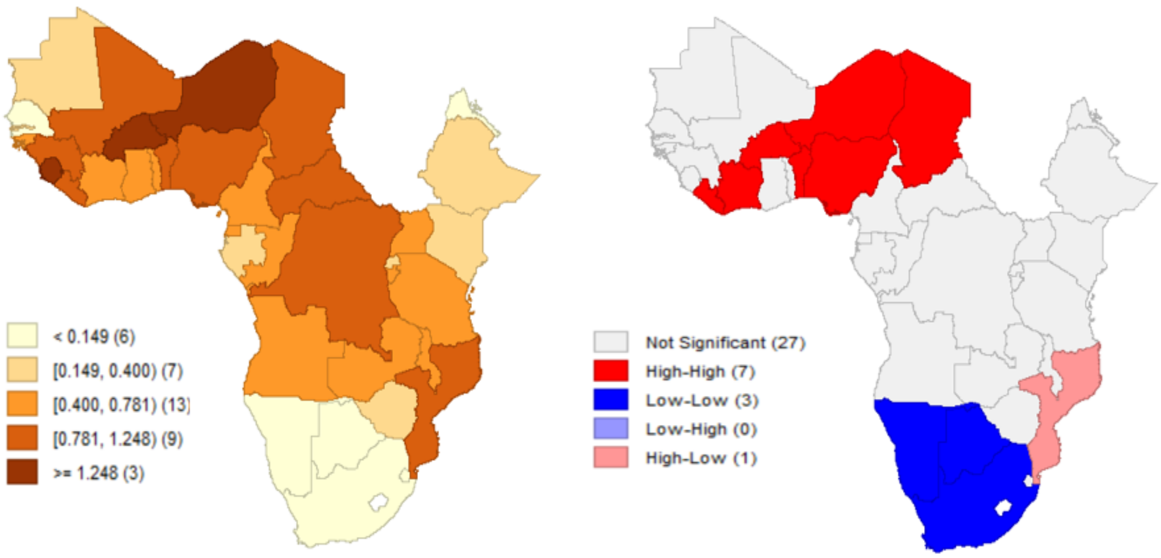


Figure D.6: Spatial Distribution and Hotspot Analysis of Malaria Deaths per 1000



D.3.2 Baseline Regression Analysis of Malaria Cases and Deaths

Baseline model results are shown in Table D.7 in the appendix. The panel FE models showed significant positive associations with health worker density, DAH, government effectiveness, and precipitation, and negative associations with GNI per capita and ANC4. By contrast, the pooled OLS model showed a positive association only for precipitation, with negative associations for GNI per capita, government effectiveness, and effective treatment.

Results from the lagged panel model are presented in Table D.8 in the appendix. Consistent with baseline models, Health worker density and government effectiveness exhibit positive associations, and GNI per capita shows a significant negative association with malaria burden. DAH shows a negative association, though the coefficient is insignificant.

We estimated elasticities for key variables to assess the relative magnitude of their effects on malaria burden, based on the baseline regression coefficients. Table D.1 shows that a 1 per cent increase in ITN access is associated with a 0.08 per cent reduction in malaria cases and a 0.18 per cent reduction in deaths. These estimates indicate a lower disease burden associated with ITN access. Health worker density shows negative elasticities for both outcomes, with a 1 per cent increase associated with 0.56 per cent and 0.93 per cent reductions in cases and deaths, respectively. However, the marginal effects for health worker density are positive, suggesting a simultaneous increase in the number of detected cases. DAH per capita also shows negative elasticities (-0.29% for cases and -0.39% for deaths) but positive marginal effects. The discrepancy between negative elasticities and positive margins suggests that DAH is often allocated in response to burden, with health benefits emerging over longer timeframes. Antenatal care coverage (ANC4) demonstrates strong and consistent protective elasticities, with a 1 per cent increase associated with 1.94 per cent reductions in both cases and deaths. Indoor residual spraying (IRS) coverage shows no significant effects in either elasticity or marginal estimates.

Table D.1: Elasticities and Margins per Percentage Point Change in Intervention

Variables	Elasticity		Margins	
	Cases	Deaths	Cases	Deaths
ITN-Access	-0.08*	-0.18***	-0.01***	-0.01***
	(0.04)	(0.04)	(0.01)	(0.01)
IRS coverage	-0.00	0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Health worker density per 100000	-0.56**	-0.93***	7.31***	1.07
	(0.27)	(0.19)	(1.22)	(0.79)
DAH per capita	-0.29**	-0.39***	0.53***	0.52***
	(0.11)	(0.09)	(0.06)	(0.08)
ANC4	-1.94***	-1.94***	-7.68***	-9.09***
	(0.67)	(0.67)	(1.75)	(1.25)

D.3.3 Panel Regression Analysis of Malaria Cases and Deaths

Panel regression models using fixed effects with Driscoll–Kraay standard errors were used to address serial correlation, heteroskedasticity, and cross-sectional dependence. Additionally, panel regressions with panel-corrected standard errors and robust clustering were employed to ensure the robustness of the findings. The results in Table D.2 show that with regard to health worker density, there is a significant positive association with malaria cases across all specifications. Similar magnitudes are observed for malaria deaths (Table D.3), though the coefficients become insignificant and negative when using panel-corrected standard errors. DAH, government effectiveness and precipitation show a positive and significant association with both malaria cases and deaths, though government effectiveness is insignificant for malaria deaths. Antenatal care attendance and ITN access show consistent negative associations with both malaria cases and deaths. Urbanisation demonstrates strong protective effects against malaria cases. IRS coverage demonstrates no statistically significant association with either malaria cases or deaths across all analytical specifications.

Table D.2: Panel Regression Analysis for Malaria Cases per 1000

DV: Malaria cases per 1000 (log)	(1) Driscoll-Kraay	(2) Driscoll-Kraay with 1 lag	(3) FE-Robust Country	(4) Panel correlated SEs	(5) FE-Robust
Health Worker Density (log)	6.98***	6.98***	6.98**	4.54*	6.98**
	(1.34)	(1.44)	(3.10)	(2.39)	(3.10)
IRS Coverage	0.01	0.01	0.01	0.00	0.01
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
ITN-Access	-0.00**	-0.00**	-0.00*	0.01***	-0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DAH per capita (log)	0.54***	0.54***	0.54**	0.55***	0.54**
	(0.06)	(0.07)	(0.23)	(0.11)	(0.23)
Precipitation (log)	0.45***	0.45**	0.45**	0.73***	0.45**
	(0.14)	(0.15)	(0.21)	(0.09)	(0.21)
Urbanicity	-49.04***	-49.04***	-49.04*	-34.85*	-49.04*
	(10.57)	(11.86)	(24.26)	(20.83)	(24.26)
ANC4	-7.83***	-7.83***	-7.83	-4.34	-7.83
	(1.74)	(2.01)	(5.20)	(3.49)	(5.20)
GNIpc (log)	-0.63***	-0.63***	-0.63*	-1.02***	-0.63*
	(0.11)	(0.11)	(0.35)	(0.09)	(0.35)
Government Effectiveness Index	0.37**	0.37**	0.37*	-0.79***	0.37*
	(0.13)	(0.14)	(0.21)	(0.19)	(0.21)
Effective Treatment	0.00	0.00	0.00	-0.01***	0.00
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Observations	494	494	494	494	494
R-squared			0.12	0.63	0.12
Number of countries	38	38	38	38	38

Notes: Standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively

Table D.3: Panel Regression Analysis for Malaria Deaths per 1000

DV: Malaria Deaths per 1000 (log)	(1) Driscoll-Kraay	(2) Driscoll-Kraay with 1 lag	(3) FE-Robust Country	(4) Panel correlated SEs	(5) FE-Robust
Health Worker Density (log)	1.37	1.37	1.37	-2.07	1.37
	(0.88)	(1.40)	(2.03)	(2.77)	(2.03)
IRS Coverage	0.00	0.00	0.00	-0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
ITN-Access	-0.00**	-0.00**	-0.00***	0.01***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DAH per capita (log)	0.52***	0.52***	0.52**	0.50***	0.52**
	(0.08)	(0.10)	(0.23)	(0.13)	(0.23)
Precipitation (log)	0.30*	0.30*	0.30*	0.50***	0.30*
	(0.14)	(0.17)	(0.15)	(0.09)	(0.15)
Urbanicity	-5.92	-5.92	-5.92	19.07	-5.92
	(7.14)	(11.70)	(18.10)	(24.62)	(18.10)
ANC4	-8.96***	-8.96***	-8.96*	-8.13*	-8.96*
	(1.36)	(1.72)	(4.99)	(4.17)	(4.99)
GNIpc (log)	-0.50***	-0.50***	-0.50**	-0.94***	-0.50**
	(0.15)	(0.15)	(0.24)	(0.11)	(0.24)
Government Effectiveness Index	0.12	0.12	0.12	-0.64***	0.12
	(0.07)	(0.07)	(0.17)	(0.14)	(0.17)
Effective treatment	-0.00	-0.00	-0.00	-0.01***	-0.00
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Observations	494	494	494	494	494
R-squared			0.20	0.38	0.20
Number of groups	38	38	38	38	38

Notes: Standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively.

D.3.4 Spatial Regression Analysis of Malaria Cases and Deaths

Before estimating spatial regression models, spatial autocorrelation in malaria cases and deaths was assessed using Moran's I statistics. In Table D.6 of the appendix, the Z scores and p-values indicate that spatial autocorrelation in malaria outcomes per 1000 is significant at the 1 and 5 per cent level across all years. The positive Moran's I values indicate that countries with high malaria cases and deaths per 1000 (countries in the high-high groups) tend to cluster together, as do the low-burden countries (countries in the low-low groups). For malaria deaths per 1000, there is persistent, positive spatial autocorrelation across SSA countries during the study period. The values range from 0.36 to 0.46, suggesting that countries with high malaria mortality are geographically clustered, as are those with low incidence. From 2010 to 2014, Moran's I values remain relatively stable around 0.36, indicating moderate but consistent clustering of malaria outcomes during these years, but increase above 0.40 after 2014. Regarding malaria cases per 1000, there exists positive spatial autocorrelation from 2010 to 2022. The results of the LISA cluster analysis using Local Moran's I are shown in Figures D.5 and D.6. Significant positive values indicate hotspots (high-high clusters), while significant negative values indicate cold spots (low-low clusters).

The local effects from the spatial regression models align with results obtained from the Driscoll-Kraay FE models. Table D.4 shows that higher health worker density, DAH and precipitation are associated with increased malaria cases and deaths. Higher values of government effectiveness are associated with higher values of malaria cases. ANC, GNIpc and ITN access show negative associations with malaria cases and deaths. IRS Coverage and effective treatment show no significant association with malaria outcomes. Spatial analysis confirms the presence of spillover effects (Wald tests: $p<0.05$), though their nature differs between cases and deaths. These effects operate primarily through intervention spillovers rather than direct disease transmission.

For malaria deaths, neighbouring countries' health resources generate significant spillover benefits: higher health worker density and DAH in adjacent countries reduce local deaths, indicating that health system strengthening in one country can benefit neighbouring countries. However, higher ANC4 coverage in neighbouring areas shows a positive association with local malaria deaths and cases. Malaria cases show weaker spatial spillovers and respond primarily to local conditions rather than neighbouring-country factors. The non-significant spatial lag coefficients for the dependent variables indicate that once we control for the spatial distribution of interventions and covariates, malaria burden in neighbouring countries does not directly predict local burden. This suggests that spatial effects and patterns may operate through intervention spillovers and risk factors rather than through cross-border disease transmission.

Table D.4: Spatial Regression Models

	DV: Malaria deaths per 1000 (log)			DV: Malaria cases per 1000 (log)		
Variables	**SLX**	**SDM**	**SDEM**	**SLX**	**SDM**	**SDEM**
Health Worker Density (log)	3.90*	3.96*	3.94*	8.59***	8.45***	8.93***
	(2.31)	(2.32)	(2.37)	(2.73)	(2.73)	(2.93)
IRS Coverage	0.00	0.00	0.00	0.01*	0.01*	0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ITN-Access	-0.00**	-0.00**	-0.00**	-0.01**	-0.00**	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DAH per capita (log)	1.13***	1.13***	1.12***	1.01**	1.01**	1.01**
	(0.34)	(0.34)	(0.34)	(0.40)	(0.40)	(0.40)
Precipitation (log)	0.33**	0.32**	0.33**	0.44***	0.44***	0.46***
	(0.15)	(0.15)	(0.15)	(0.17)	(0.17)	(0.18)
Urbanicity	-8.61	-9.18	-9.13	-55.76**	-53.55**	-57.52**
	(20.11)	(20.12)	(20.07)	(24.21)	(23.70)	(25.62)
ANC4	-23.79***	-23.72***	-23.67***	-17.88***	-18.55***	-18.16***
	(5.77)	(5.77)	(5.81)	(6.87)	(6.81)	(6.95)
GNIpc (log)	-0.48***	-0.48***	-0.48***	-0.66***	-0.64***	-0.65***
	(0.14)	(0.14)	(0.14)	(0.17)	(0.17)	(0.17)
Government Effectiveness Index	0.13	0.14	0.13	0.36***	0.37***	0.36***
	(0.11)	(0.11)	(0.11)	(0.13)	(0.13)	(0.13)
Effective treatment	0.01	0.01	-0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
W*Health Worker Density (log)	-3.02***	-3.00***	-3.01***	-1.09	-1.34	-1.29
	(1.03)	(1.03)	(1.04)	(1.22)	(1.23)	(1.26)
W*ITN-Access	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
W*DAH per capita (log)	-0.79**	-0.82**	-0.79**	-0.62	-0.66	-0.61
	(0.40)	(0.40)	(0.40)	(0.47)	(0.47)	(0.48)
W*ANC4	20.29***	20.49***	20.19***	14.37**	15.87**	14.99**
	(6.12)	(6.12)	(6.16)	(7.24)	(7.31)	(7.37)
W* Government Effectiveness	-0.16	-0.15	-0.16	-0.22	-0.21	-0.22
	(0.27)	(0.27)	(0.27)	(0.32)	(0.32)	(0.33)
W*Malaria deaths per 1000 people		0.05			0.12	
		(0.09)			(0.09)	
W*Malaria cases per 1000 people						
e.log_malaria_deaths_per_1000			0.04			
			(0.09)			
e.log_malaria_cases_per_1000						0.11
						(0.09)
Wald Chi2	127.84***	129***	121.9***	78.15***	80.25***	72.60***
Wald test of spatial terms Chi2	12.44**	12.78**	12.49*	12.96**	14.71**	13.90**
Log-likelihood	-77.55	-77.39	-77.46	-153.04	-152.32	-152.23
AIC	187.10	188.78	188.91	338.09	338.46	338.64
BIC	254.35	260.23	260.35	405.33	409.91	410.08

Notes: Standard errors in parentheses, 38 countries, Observations=494. ***, **, * significant at the 1, 5, and 10%-level respectively.

D.3.5 Robustness Checks

Different robustness checks were run to confirm the validity of the main results. First, a model incorporating potential structural breaks that could have been caused by COVID-19, by excluding data from 2020 and 2021. The unprecedented global disruption caused by the COVID-19 pandemic significantly affected health systems and disease surveillance infrastructure. Then, the exclusion of Southern African countries was tested to see whether results hold across different regional epidemiological contexts, given their lower malaria endemicity. Real-world relationships between health system variables and disease outcomes often show non-linearity due to diminishing returns, threshold effects, or saturation. Quadratic terms for health worker density and DAH were included to assess whether their effects on malaria burden change at higher levels. The effects of health worker density, DAH, and governance effectiveness on malaria burden are robust across model variations and time periods. However, the findings are not robust to using the case fatality ratio (CFR), the ratio of malaria deaths to reported cases, as an outcome variable, rather than examining cases and deaths separately. The results are shown in Tables D.9 and D.10 in the appendix.

D.4 Discussion

DAH shows a positive association with malaria burden, indicating targeted aid allocation to high-burden countries and improved reporting due to donor-supported monitoring systems (Dieleman et al., 2019; Lu et al., 2010; Micah et al., 2019; Odokonyero et al., 2018; Ravishankar et al., 2009). Additional aid produces greater health improvements in countries (Sempungu et al., 2023). However, the findings contrast with previous studies, which found that targeted DAH is associated with reductions in malaria mortality (Dieleman et al., 2016; Shretta et al., 2016). The effectiveness of such assistance is likely contingent upon national governance quality, institutional readiness, and the timeliness of implementation.

Government effectiveness associates positively with malaria case detection, reinforcing the view that improved governance enhances surveillance and reporting systems rather than directly reducing transmission or mortality (Holmberg et al., 2009). Increasing health worker density, which increases the malaria burden, reflects the role of health systems in both detecting and treating malaria, where improved surveillance leads to higher observed incidence despite overall reductions in disease severity and mortality (Alhassan & Wills, 2024; Okoroafor et al., 2022). This pattern aligns with prior studies showing that stronger health systems can inflate disease burden metrics through better detection (WHO, 2023). ITN access and antenatal care coverage (ANC4) are negatively associated with malaria cases and deaths (Hill et al., 2013). ITN access has a role in preventing malaria transmission and severe outcomes (Lengeler, 2004; Pryce et al., 2018; Wilson et al., 2014). Indoor residual spraying (IRS) coverage, which shows no significant relationship with malaria outcomes, likely reflects operational challenges, subnational heterogeneity in implementation, and growing insecticide resistance, which undermine IRS effectiveness (Hemingway et al., 2016; Pluess et al., 2010).

Environmental factors confirm established epidemiological patterns, with precipitation increasing malaria burden through creating favourable conditions for vector breeding and transmission cycles (Kebede et al., 2005; Pabon-Rodriguez & Ayodo, 2025; Woyessa et al., 2023). Urbanisation lowers malaria incidence by improving housing and reducing vector habitats, but its inconsistent effects on mortality suggest disparities in healthcare access or treatment quality within urban populations (Hay et al., 2005; Iormom et al., 2023; Tatem et al., 2013). GNI per capita shows consistent negative relationships with both malaria incidence and mortality, confirming the fundamental role of economic development in reducing disease burden. Higher income levels facilitate improvements in housing quality, nutritional status, healthcare access, and public health infrastructure, collectively reducing malaria risk and improving treatment outcomes (Gallup & Sachs, 2001; Villena et al., 2024).

Higher health worker density and development assistance in surrounding regions reduce local malaria mortality, indicating cross-border health benefits. The positive association of antenatal care coverage in neighbours with local malaria deaths and cases likely reflects spatial clustering of reporting patterns. Spatial spillovers in malaria cases are less pronounced, suggesting that cases respond more to local conditions. The limitations of the study include the study's restriction to national-level panel data for the set of health system and intervention variables over the study period. It does not assess intervention quality, community-level factors, or entomological indicators. Future research should integrate subnational panel data to capture geographic heterogeneity at that level. The study examines only aggregate development assistance without distinguishing between intervention types, limiting the ability to identify which aid funding streams are most effective. Future research should disaggregate aid data to assess the relative impacts.

D.5 Conclusion

The study concludes that malaria cases and deaths in SSA are mainly influenced by local factors rather than by direct spatial dependence on neighbouring countries' disease levels. Among local determinants, health worker density, DAH, government effectiveness, and precipitation are positively associated with the malaria burden. ITN access, ANC4 coverage, and income show protective elasticities for malaria cases and deaths. Beyond local effects, spatial spillovers emerge through intervention coverage. Neighbouring countries' health worker density and DAH reduce local malaria deaths, demonstrating cross-border benefits from health investments, though antenatal care coverage increases the local malaria burden. Therefore, malaria control strategies should focus on local health system strengthening alongside regional resource coordination, recognising spatial patterns in both health service distribution and environmental risk.

D.6 References

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D.7 Appendix

Table D.5: Variables, Measurements, Definitions, and Descriptive Statistics.

Variables	Unit of measurement	Definition of the variables	Obs	mean	sd	min	p50	max
Malaria deaths per 1000	Rate	Malaria deaths per 1000 population	494	0.54	0.43	0.001	0.46	2.37
Malaria cases per 1000	Rate	Malaria cases per 1000 population	494	216.14	139.97	0.03	231.61	709.79
Government effectiveness	Index rescaled from − 2.5 to + 2.5 to range from 0 to 1	The index of government effectiveness captures political stability, rule of law and government effectiveness. Source: World Bank Governance Indicators	494	0.44	0.22	0	0.44	1
Health Worker Density	Ratio	Number of employed health workers (of any specialty) per 100,000 population	494	41.59	5.03	34.15	41.34	49.92
DAH percapita	Amount	DAH per person (2022 USD)	494	19.92	4.01	16.5	18.18	29.76
Precipitation	Precipitation	Annual precipitation in mm. Source: WB Climate Change Knowledge Portal	494	94.28	50.14	7.76	88.58	240.85
LGNIpc		Gross National Income percapita	494	7.95	0.79	6.57	7.69	9.84
ITN-access	Percentage	Percentage of population accessing ITNs/LLIns	494	43.77	23.79	0	46.71	91.25
ANC4	Proportion	Proportion of pregnant women receiving 4 or more antenatal care visits including 1 or more from a skilled provider	494	0.59	0.02	0.56	0.58	0.65
Effective Treatment	Percentage	Effective treatment in 100 malaria cases	494	43.07	12.82	12.20	43.04	71.66
IRS coverage	Percentage	Percentage of households covered with Indoor Residual Spraying	494	4.21	6.96	0	0.99	42.14
Urbanicity	Proportion	Proportion of Urban Population	494	0.26	0.02	0.24	0.26	0.29
Years of Education	Count	Average Years of Education	494	5.04	2.38	1	5	12

Table D.6: Malaria Cases and Deaths per 1000 Global Moran's I statistics.

Malaria Deaths per 1000													
year	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Moran's I	0.360	0.386	0.360	0.359	0.360	0.410	0.437	0.457	0.460	0.458	0.428	0.420	0.413
Z-Score	3.251	3.457	3.225	3.216	3.203	3.631	3.866	3.996	4.019	3.999	3.761	3.693	3.638
p-value	0.0012	0.0005	0.0013	0.0013	0.0014	0.0003	0.0001	0.0001	0.0001	0.0001	0.0002	0.0002	0.0003
Malaria Cases per 1000													
Moran's I	0.385	0.370	0.335	0.316	0.347	0.346	0.373	0.307	0.386	0.413	0.390	0.372	0.346
Z-Score	3.367	3.243	2.957	2.802	3.056	3.052	3.265	2.813	3.372	3.589	3.405	3.254	3.041
p-value	0.0008	0.0012	0.0031	0.0051	0.0022	0.0023	0.0011	0.0049	0.0007	0.0003	0.0007	0.0011	0.0024

Table D.7: Baseline Regression Results (Panel FE and Pooled OLS Regressions)

	Malaria Cases per 1000 (log)		Malaria Deaths per 1000 (log)	
Variables	FE	Pooled OLS	FE	Pooled OLS
Health Worker Density (log)	6.98***	-5.78	1.37	-10.31
	(2.58)	(9.07)	(2.18)	(7.28)
IRS Coverage	0.01*	-0.01	0.00	-0.02**
	(0.00)	(0.01)	(0.00)	(0.01)
ITN-Access	-0.00**	0.04***	-0.00**	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)
DAH per capita (log)	0.54***	0.54	0.52***	0.49
	(0.19)	(0.70)	(0.16)	(0.56)
Precipitation (log)	0.45**	0.65***	0.30**	0.38***
	(0.18)	(0.09)	(0.15)	(0.08)
Urbanicity	-49.04**	30.61	-5.92	67.60
	(23.27)	(84.22)	(19.71)	(67.60)
ANC4	-7.83*	-2.62	-8.96**	-5.06
	(4.21)	(15.76)	(3.57)	(12.65)
GNIpc (log)	-0.63***	-0.50***	-0.50***	-0.49***
	(0.17)	(0.10)	(0.14)	(0.08)
Government Effectiveness Index	0.37***	-0.84***	0.12	-0.80***
	(0.14)	(0.15)	(0.12)	(0.12)
Effective treatment	0.00	-0.02***	-0.00	-0.02***
	(0.01)	(0.01)	(0.01)	(0.00)
Observations	494	494	494	494
R-squared	0.12	0.59	0.20	0.63
Number of countries	38	38	38	38

Notes: Standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively.

Table D.8: Panel Regression for Malaria Cases and Deaths per 1000 based on Lagged Values

Variables	(1) Malaria Cases	(2) Malaria Deaths
L.Health Worker Density (log)	8.62***	4.90**
	(2.54)	(2.20)
L.IRS Coverage	0.00	-0.00
	(0.00)	(0.00)
L.ITN-Access	-0.00*	-0.00**
	(0.00)	(0.00)
L.DAH per capita (log)	-0.09	-0.14
	(0.19)	(0.17)
Precipitation (log)	0.28	0.28*
	(0.18)	(0.16)
L.Urbanicity	-73.00***	-45.02**
	(22.92)	(19.88)
L.ANC4	3.12	4.10
	(4.38)	(3.80)
L.GNIpc (log)	-0.66***	-0.50***
	(0.18)	(0.16)
L.Government Effectiveness Index	0.54***	0.22*
	(0.15)	(0.13)
Effective treatment	0.01	-0.01
	(0.01)	(0.01)
Observations	456	456
R-squared	0.11	0.14
Number of countries	38	38

Notes: Standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively. L. represents variables lagged by one year.

Table D.9: Robustness Tests: Malaria Cases per 1000

Variables	DV: Case Fatality Ratio	DV: Malaria cases per 1000 (log) SDM	Exclusion of COVID-time	No Southern Africa
Health Worker Density (log)	-0.03	8.43***	8.96***	4.57***
	(0.02)	(2.75)	(2.92)	(0.64)
Health Worker Density (log)^2		-0.01*		
		(0.00)		
DAH per capita (log)^2		0.00		
		(0.00)		
IRS Coverage	0.00	0.01*	0.01**	0.01
	(0.00)	(0.00)	(0.00)	(0.00)
ITN-Access	0.00	-0.00***	-0.00**	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
DAH per capita (log)	0.01	0.36	1.08**	0.21***
	(0.01)	(1.04)	(0.43)	(0.05)
Precipitation (log)	-0.00	0.48***	0.38*	0.19
	(0.00)	(0.17)	(0.20)	(0.14)
Urbanicity	0.42**	142.35	-55.08**	-33.67***
	(0.18)	(105.67)	(25.36)	(4.96)
ANC4	-0.14***	-22.99***	-18.94***	-3.10**
	(0.05)	(8.23)	(7.19)	(1.39)
GNIpc (log)	0.00	-0.67***	-0.63***	-0.60***
	(0.00)	(0.17)	(0.20)	(0.08)
Government Effectiveness Index	-0.00	0.37***	0.46***	0.30**
	(0.00)	(0.13)	(0.16)	(0.13)
Effective treatment	-0.00	0.01	0.01	0.01
	(0.00)	(0.01)	(0.01)	(0.01)
W*Health Worker Density (log)	-0.02**	-1.05	-1.37	
	(0.01)	(1.22)	(1.31)	
W*Government effectiveness	-0.00	-0.00	-0.00	
	(0.00)	(0.01)	(0.01)	
W*ITN-Access	0.00	-0.00	-0.00	
	(0.00)	(0.00)	(0.00)	
W*DAH per capita (log)	-0.01	-0.69	-0.77	
	(0.01)	(0.47)	(0.51)	
W*ANC4	0.11**	15.11**	15.96**	
	(0.05)	(7.30)	(7.71)	
W*DV	-0.10	0.11	0.13	
	(0.11)	(0.09)	(0.10)	
Observations	494	494	418	442
Number of groups	38	38	38	34
Wald Chi2	14.09	84.13	61.13	
Prob > Chi2	0.339	0.000	0.000	

Notes: Standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively.

Table D.10: Robustness tests: Malaria Deaths per 1000

DV: Malaria deaths per 1000 (log)	SDM	Exclusion of COVID-time	No Southern Africa
Health Worker Density (log)	3.92*	3.85	0.75
	(2.31)	(2.46)	(0.99)
Health Worker Density (log)^2	-0.01**		
	(0.00)		
DAH per capita (log)^2	0.00		
	(0.00)		
IRS Coverage	0.00	0.00	0.00***
	(0.00)	(0.00)	(0.00)
ITN-Access	-0.00***	-0.00**	-0.00**
	(0.00)	(0.00)	(0.00)
DAH per capita (log)	0.42	1.21***	0.16***
	(0.88)	(0.36)	(0.04)
Precipitation (log)	0.35**	0.24	0.26***
	(0.15)	(0.17)	(0.08)
Urbanicity	-28.48***	-8.36	-8.10
	(6.96)	(21.35)	(7.48)
ANC4	-28.48***	-23.18***	-1.49
	(6.96)	(6.05)	(1.31)
GNIpc (log)	-0.50***	-0.48***	-0.56***
	(0.14)	(0.17)	(0.12)
Government Effectiveness Index	0.14	0.13	0.06
	(0.11)	(0.13)	(0.04)
Effective treatment	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)
W*Health Worker Density (log)	-2.74***	-2.94***	
	(1.04)	(1.10)	
W*Government effectiveness	-0.13	-0.19	
	(0.27)	(0.34)	
W*ITN-Access	-0.00	-0.00	
	(0.00)	(0.00)	
W*DAH per capita (log)	-0.82**	-0.91**	
	(0.40)	(0.43)	
W*ANC4	19.10***	20.02***	
	(6.10)	(6.41)	
W*Malaria cases per 1000 people	0.03	0.05	
	(0.09)	(0.10)	
Observations	494	418	442
Number of groups	38	38	34
Wald Chi2	134.7	97.84	
Prob > Chi2	0.000	0.000	

Notes: Standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively.

E Can Schooling Reduce Inequality? Evidence from Two Centuries of Compulsory Education[4]

Abstract

Compulsory education (CE) laws broadened access to schooling worldwide and reshaped patterns of human capital formation, thereby affecting a range of economic, social, and health outcomes. However, the extent to which these policies reduced long-term health inequalities remains unclear. We study the effect of introducing CE policies on health inequality, drawing on height inequality data from 62 countries between 1810 and 2000 and using a staggered difference-in-differences design to estimate intent-to-treat effects of CE on health disparities. Our results show that while CE reduced height inequality, its effectiveness depended on institutional conditions, particularly a country's administrative capacity to enforce school attendance. We document that the most significant impacts occurred in Europe, driven by higher average educational attainment and lower child mortality. Overall, the findings suggest that education policies can meaningfully narrow health disparities over time, but their success hinges on both the institutional environment and the timing of adoption.

[4] This chapter is based upon joint work with Alberto Batinti, Joan Costa-Font and Jörg Baten. I contributed approximately 70 per cent to this research paper.

E.1 Introduction

The expansion of formal education systems has played a critical role in developing human capital and in fostering the transmission of social skills and health information, factors that can shape health outcomes later in life (Courtin et al, 2019) and help reduce socio-economic inequalities across generations (Andersen et al., 2021; Card et al., 2018). The fundamental goals of educational curriculum design are to promote beneficial later-life routines, fostering reading habits and understanding of the world, as well as supporting the stability of a political system, encouraging responsible citizenship, and mitigating conflict and long-term outcomes, including lifelong health and fitness. Historically, the expansion of formal education systems occurred through multiple policy interventions that involved public financing to expand infrastructure and teacher training (Goldin & Katz, 2008b) and most importantly the introduction of compulsory education (CE) laws mandating school attendance for specified age ranges was one of the significant policy tools that helped expand education (Murtin & Viarengo, 2011; Oreopoulos, 2006). Throughout the 17th to 20th centuries, countries worldwide gradually implemented various forms of CE laws[5].

Existing research has extensively documented evidence of the economic returns of compulsory schooling (Angrist & Krueger, 1991; Clay et al., 2021; Lindert, 2004; Oreopoulos, 2006; Oreopoulos & Salvanes, 2011). Beyond economic returns[6], CE reduces crime rates, social unrest, and political extremism, and improves health outcomes (Lindert, 2004; Oreopoulos, 2007; Oreopoulos & Salvanes, 2011). Lleras-Muney (2002) demonstrated that compulsory school attendance and child labour laws in the United States increased educational attainment, with effects concentrated among those in the lower percentiles of the education distribution. Education can influence human capital accumulation, which, in

[5] These reforms arose from a range of civic and government interests which included the development of an educated electorate capable of meaningful participation in a democratic process (Gallego, 2010; Milligan et al., 2004). In many cases, compulsory education (CE) was also used to foster national identity and a common language in a largely fragmented Europe, while building a structured and effective military force by ensuring a steady supply of literate and trained soldiers (Ramirez & Boli, 1987; Weber, 1976)

[6] Nonetheless, beyond political objectives, education systems aimed to develop skills (e.g., personal discipline), and literacy to support economic growth and national development (Glaeser et al., 2007).

turn, affects an individual's health production function, as conceptualised in Grossman's (1972) work[7]. Hence, it is an empirical question whether education expansion reduced health inequality. So far, we know less about the effects of CE on health inequality.

Research shows that one additional year of education reduces mortality rates (Lleras-Muney, 2005), and Glied & Lleras-Muney (2008) showed that education gradients in health outcomes have widened over time, as more educated individuals are better positioned to adopt health-improving innovations. However, these studies draw primarily on evidence from developed countries, and the magnitude of inequality-reducing effects depends critically on infrastructure expansion, education quality, and access in underserved and rural areas, which vary quite widely across the world (Burde & Linden, 2013; Duflo, 2001; Glewwe & Muralidharan, 2016; Hanushek & Woessmann, 2012). One way to study these effects is to adopt a historical perspective and examine cross-country evidence of the introduction of CE on retrospective measures of health inequality.

This paper examines the effect of the introduction of CE regulations across 62 countries between 1810 and 2000 on health inequality, using height inequality data. We use a staggered difference-in-differences design to estimate intent-to-treat effects, examine heterogeneous effects across multiple dimensions, and conduct robustness checks. The effectiveness of CE policies in reducing inequality hinged on the economic calculus faced by low-income families regarding child labour.[8] Where the opportunity costs of school attendance were prohibitively high, families made economically rational decisions to rely on child earnings. CE laws proved most effective when complemented by policies that reduced the financial burden of school attendance on resource-constrained households. Studies have shown that where CE was paired with financial support programs for low-income families, child labour rates decreased

[7] Grossman's model posits that education improves allocative efficiency in health production by enabling individuals to better process and utilise health information.

[8] Families faced an intertemporal trade-off between immediate income from child labour and higher future returns from educational investment. Historically, enforcement of CE has been closely linked to reductions in child labour, as these regulations delayed children's entry into the labour market and enabled accumulation of human capital necessary for more productive adult employment (Edmonds & Pavcnik, 2005).

significantly and school enrolment rates improved substantially (Basu & Van, 1998; Beegle et al., 2009).

CE may widen health inequalities if educational resources are not distributed equitably (Zajacova & Lawrence, 2018) or if there are wide variations in school quality across regions and socioeconomic environments (Barcellos et al., 2023; Whitty, 1998), limiting the health returns to education. The economic growth and urbanisation that often accompany educational expansion might initially increase inequality as benefits temporarily accrue unevenly, initially targeting the most affluent segments of the population (Dabla-Norris et al., 2015). Yang & Qiu (2016) found that CE in China widened the human capital gap between wealthy and poor children, driven by unequal family investments in early education and differential school quality. Historical evidence demonstrates that the effects of CE are substantially amplified when accompanied by complementary policies such as the expansion of schooling infrastructure, subsidisation of education costs, and improved school availability in underserved areas (Goldin & Katz, 2008b)[9]. School quality improvements were particularly beneficial for children from less educated backgrounds after the introduction of compulsory schooling mandates (Card et al., 2018).

Therefore, the potential of CE to yield significant benefits depends on the ability to address multiple structural barriers that may prevent all children from fully participating in the education system, including economic barriers, such as the opportunity costs of foregone child labour income, and social barriers, such as caste hierarchies or institutionalised discrimination. Educational attainment may not translate into improved economic outcomes for marginalised groups, thereby undermining the inequality-reducing potential of CE laws. When these barriers are addressed, CE disproportionately benefits low-income groups by improving access to health information, equipping individuals with skills to adopt healthy

[9] The American high school movement of 1910-1940 illustrated the synergy where the combination of compulsory attendance laws, dramatic expansion in the number of secondary schools, and public financing enabled secondary school graduation rates to increase. The surge in the number of local high schools in the early 1950s exemplifies the critical role of infrastructure development in facilitating educational access (Doxey et al., 2022).

behaviours and delay risky activities (Kenkel, 1991; Brunello et al., 2016), and fostering intergenerational mobility that reduces social inequality.

We contribute to the literature as follows. First, we study how the gradual implementation of CE reforms over time affects an objective measure of retrospective health: individual heights. This measure is widely regarded as free from manipulation and offers a reliable indicator of long-term health outcomes. Unlike previous studies, we exploit evidence of the historical expansion of CE reforms across countries, and particularly at times when baseline literacy levels were low[10]. Despite growing research on CE policies and health, no studies have examined whether CE policies affect height inequality within populations. This gap is significant, as height disparities reflect unequal access to nutrition and healthcare during critical growth periods. Height serves as an anthropometric measure for assessing nutritional status, health conditions, and socioeconomic circumstances during childhood and adolescence[11]. We document evidence that the introduction of CE historically reduced the Gini index calculated on the country-level distribution of human heights. The findings also reveal relevant regional heterogeneity, suggesting that local factors shape the extent of the policy's impact.

Second, our research contributes to the ongoing study of the historical effects of education reforms, specifically focusing on outcomes that are still poorly understood. By examining the long-term consequences of these reforms on a measure of retrospective health, we shed light on this question and fill a gap in the literature on how educational policies can influence health inequality across settings. To our knowledge, this is the first paper to address

[10] In this context, such reforms would have likely played a critical role in disseminating vital health information that enhanced individual survival rates, an area that has been underexplored in terms of its impact on health disparities.

[11] The measure correlates with various health indicators (Fogel, 1994; Steckel, 1995) and predicts economic outcomes such as income and wages (Persico et al., 2004; Strauss & Thomas, 1998). These economic returns to height operate partly through cognitive abilities, which themselves are shaped by early-life health and nutrition (Case et al., 2002). In this paper, we examine the effect of the introduction of CE on health inequality, measured by the distribution of human height, which is a retrospective proxy of individuals' well-being (Akachi & Canning, 2015; Baten & Blum, 2012; Pradhan et al., 2003).

the effects of CE on health inequality from a historical perspective, specifically over two centuries.

Finally, our study examines the long-term effects of CE policies via multiple potential pathways. More specifically, drawing on the best available evidence, we identify and evaluate plausible mechanisms through which educational reforms could have influenced health outcomes, thereby helping us better understand the link between education and health inequality. We investigate the effects of child mortality, schooling, and democracy as potential mechanisms. The next section discusses the literature to which this paper contributes. Section three presents the data, measures and empirical strategy. Then, we report the results and mechanisms in section four, and section five reports on the tests of heterogeneity, placebo tests and robustness; the final section six concludes.

E.2 Related Literature

E.2.1 Height as a Measure of Health

Anthropometric indicators have become valuable tools for evaluating retrospective population health and living standards. Steckel (2009) argues that adult height reflects the cumulative effects of nutrition, disease exposure, and environmental conditions experienced during childhood and adolescence, offering insights into inequalities that monetary indicators may fail to capture (Komlos, 1998). Unlike income or consumption measures, height reveals the biological consequences of deprivation during key developmental periods, making it particularly useful for assessing long-term welfare patterns. A substantial body of research shows that taller individuals tend to earn higher wages and attain more prestigious occupations (Persico et al., 2004). Height functions as an indicator of health capital, which has direct implications for productivity and earning potential (Schultz, 2002). Moreover, Deaton (2007) documents that disparities in height within a population reflect broader forms of social inequality and uneven access to resources during early life. This paper draws on this evidence to examine whether inequalities in height are affected by cross-country expansions of CE.

E.2.2 The Education-Health Relationship

The link between education and health is well-established in health economics, with higher educational attainment consistently associated with better health outcomes and healthier behaviours. Grossman's (1972) model of the demand for health provides a central theoretical framework that includes the effects of education on information, skills and abilities. Access to information improves allocative efficiency by enabling individuals to interpret better and evaluate health information, thereby enabling the use of preventive care, nutrition, and medical treatment. However, education can enhance productive efficiency, as the cognitive and analytical skills acquired through schooling enable individuals to achieve better health outcomes.

Early work by Kenkel (1991) showed that improved health knowledge and information-processing abilities are key channels through which education shapes health behaviours. Subsequent research by Cutler and Lleras-Muney (2010) documents evidence that the cognitive and non-cognitive skills gained through schooling, such as numeracy, comprehension, and executive functioning, are important in navigating health systems and making healthier lifestyle choices. Education helps in making informed health decisions later in life. The education system influences health-related behaviours by enhancing access to health information and equipping individuals with the skills to adopt healthy routines (Brunello et al., 2016; Kenkel, 1991). Studies have found that CE reduces engagement in risky behaviours such as early smoking, alcohol consumption, and teenage pregnancies (Oreopoulos & Salvanes, 2011). For example, research in European countries found that an increase in mandatory schooling years was linked to lower rates of smoking and substance abuse in adolescence (Brunello et al., 2016). Recently, Hoque et al. (2019) examined cohort-specific data from 919 household surveys conducted between 1960 and 2012, covering 147 countries. Their study revealed that the education gradient, a consistent pattern linking higher levels of education with better health outcomes, emerges as a *universal phenomenon*[12].

[12] Specifically, they found a significant positive relationship between increased life expectancy at birth and the number of completed years of schooling across 95 per cent of the surveys analysed, including those run in post-communist countries.

Education also exerts indirect effects by influencing income, employment stability, and access to healthcare resources, which shape the structural conditions under which health behaviours develop[13]. Similarly, education enhances perceived control, self-efficacy, and long-term orientation (Ross & Wu, 1995; Mirowsky, 2017). It is worth mentioning that social networks fostered through educational and occupational environments provide additional informational and emotional resources that facilitate healthier outcomes. These pathways suggest that educational interventions may have far-reaching consequences for health equity, particularly when implemented during critical developmental periods.

Historically, curriculum design was linked to religion and disciplinary practices, emphasising obedience, loyalty and social conservatism (Cvrček, 2020; Cvrček & Zajicek, 2019; Van Horn Melton, 2003), with religion functioning as a system of social control that facilitated political stability. However, from the mid-19th century, schools gradually incorporated health-related instruction, initially focused on basic hygiene and disease prevention. This evolution continued throughout the 20th century, with some educational systems explicitly integrating health promotion. The contemporary shift toward health promotion within curricula reflects changing societal priorities. Costa-Font and Nicińska (2025) document that exposure to Communist education exerted an additional beneficial effect on health outcomes, compensating for otherwise worse health among individuals under Soviet Communism. CE enhanced children's health literacy, especially among disadvantaged children, equipping them with knowledge about hygiene, disease prevention, and healthy lifestyles[14]. That is, in this paper, we contribute to this literature by examining whether CE reforms over the last two centuries reduce persistent health inequalities, as measured by height inequalities across individuals.

[13] A fundamental goal of school curriculum design nowadays is to promote beneficial lifestyles, encompassing both immediate goals, such as fostering reading habits, supporting the political system, encouraging responsible citizenship, and mitigating conflict and long-term outcomes, including lifelong health and fitness. This represents a significant evolution from earlier educational priorities.

[14] These curricular changes have measurable health impacts: children who remain in school longer are more likely to adopt preventive health measures, such as vaccinations and regular medical check-ups (Cutler & Lleras-Muney, 2010).

E.2.3 Education and Height

Research specifically examining the relationship between education and height has produced compelling evidence of positive associations, though causal evidence remains more limited. Silventoinen et al. (2000) analysed twin data across multiple countries, demonstrating that whilst genetic factors explain most of the variation in height, environmental factors, including educational attainment, account for substantial residual differences. Their findings suggested that shared environmental factors during childhood, including educational opportunities, contribute meaningfully to adult height differences even among genetically similar individuals.

Behrman and Rosenzweig (2004) employed models to establish causal effects of birthweight on subsequent educational attainment, whilst also documenting reciprocal relationships suggesting that educational environments may influence physical development during adolescence. Their work highlighted the bidirectional nature of health-education relationships, with early health status affecting educational opportunities and educational experiences subsequently influencing ongoing physical development. Evidence also indicates that educational interventions during childhood may directly affect growth outcomes through nutritional pathways. Alderman & Bundy (2012) demonstrated that school feeding programmes generated measurable improvements in child height through changes in overall health and cognitive development, suggesting that the school environment itself serves as a platform for nutritional interventions. Cutler et al. (2008) documented that early-life circumstances are important for the coevolution of socioeconomic status and health throughout adulthood. These findings support the proposition that CE policies may influence height outcomes through both direct nutritional pathways and indirect effects on household health investments. More recently, Bharadwaj et al. (2013) examined the impact of primary school access on child health in Indonesia, finding that educational expansion improved height-for-age scores, with effects particularly pronounced among children from poorer households.

E.2.4 Distributional Effects of Compulsory Education Policies

Although some literature has explored the effects of CE on health outcomes, far less attention has been directed toward distributional consequences, particularly the implications for health inequality of CE reforms. We refer to the relationship between compulsory education (CE) and inequality as the "equalisation hypothesis", which posits that CE policies reduce disparities by imposing minimum standards of schooling exposure across socioeconomic groups. Under this hypothesis, children from disadvantaged backgrounds benefit disproportionately from CE policies, as such policies remove them from harmful environments (e.g., child labour) and provide access to school-based health services, nutritional programmes, and health education that would otherwise remain inaccessible. By mandating school attendance, compulsory education (CE) policies reduce children's participation in labour markets, a practice shown to contribute to stunted growth, malnutrition, and physical injury (Beegle et al., 2009). More broadly, extending educational opportunities can help diminish social and economic disparities by providing children from low-income households with subsidised access to skills and competencies that would otherwise lie beyond their reach. Such investments enhance their long-term economic prospects and, consequently, their health trajectories (Mayer, 1997).

Aligning with the "equalisation hypothesis", CE policies enhance intergenerational mobility by improving children's educational outcomes and labour market prospects. Parental exposure to compulsory schooling laws significantly improves their children's human capital accumulation (Oreopoulos et al., 2006). The effectiveness of CE policies is strengthened when they are accompanied by complementary measures such as free school meals and financial support for disadvantaged households (Lindert, 2004). CE policies also play a critical role in reducing gender inequality: increased school attendance among girls is associated with improved health outcomes, lower rates of child marriage, higher female labour force participation (Duflo, 2012), and significant reductions in maternal and infant mortality in many developing countries (Bhalotra & Clarke, 2013). Beyond economic and gender-related channels, CE promotes social capital and social inclusion, key determinants of health inequality, by fostering civic engagement, as demonstrated by Milligan et al. (2004), who found that extensions of CE in the U.S. and U.K. increased voter turnout and political awareness[15].

Alternatively, the "reinforcement hypothesis" posits that advantaged groups disproportionately benefit from educational expansion due to complementary resources such as parental education, financial capital, and social networks that enable them to extract greater returns from schooling (Phelan et al., 2010). Socioeconomic conditions also shape physical development, with wealthier families better able to provide nutrition and health investments that influence height, thereby contributing to persistent anthropometric disparities (Kuh & Wadsworth, 1989; Li et al., 2004). If resource-rich families respond to CE policies by further increasing complementary health inputs while poorer families face binding constraints, health inequalities may widen despite universal policy implementation. Despite extensive research on the education–health relationship and the recognised importance of height as an indicator of wellbeing, significant gaps remain in understanding how CE policies affect height inequality; while prior studies have examined CE's effects on mortality, morbidity, and health behaviours, the distributional consequences of CE for anthropometric outcomes, particularly height inequality, have not been studied.

E.3 Data and Empirical Strategy

E.3.1 Data Description

We utilise a country-level panel dataset at the decade level spanning multiple world regions, including Africa, Europe, North America, South America, and Asia, between 1810 and 2000. The final sample comprises 62 countries spanning the nineteenth and twentieth centuries, after excluding country-decade combinations with fewer than five observations on height inequality, ensuring sufficient variation to capture long-term trends. Data sources and descriptions are provided in the Appendix section E.8.1.

[15] Cross-country evidence further shows that higher educational attainment enhances political participation and reduces political inequality by encouraging electoral engagement among lower-income groups (Gallego, 2010).

E.3.2 Outcome Variable: Height-Gini

Adult height is commonly accepted as a retrospective indicator of biological well-being and adaptation (Fogel et al., 1982; Komlos, 1985; Steckel, 1995). Human stature grows most rapidly during the first three to five years of life, followed by a smaller second growth spurt during adolescence (Bogin, 2020; Tanner, 1986). This early childhood growth period is susceptible to environmental conditions, with pathogen exposure and nutritional adequacy exerting lasting effects on final adult height (Beard & Blaser, 2002). Height remains relatively stable throughout adulthood until approximately age 50, after which the skeletal structure begins to shrink due to vertebral compression and postural changes (Sorkin et al., 1999). Hence, we focus on heights measured in adulthood and aggregated by birth cohort (Baten, 1999; Eveleth and Tanner, 1976). Previous studies have shown that while genetic factors have a distinct impact on height at the individual level, population averages are influenced by diet quality and environmental/health conditions (Baten, 1999; Baten, 2000a; Komlos, 1985; Steckel, 1995; Stinson, 1985). Overall, the significant increase in population height from the 19th to the 20th century suggests that environmental factors significantly impact height, especially during the years of skeletal growth when bone plasticity is highest (Hatton & Bray, 2010).[16]

Height inequality is measured by the Gini coefficient of adult heights within each country-decade cohort (Height Gini). It is an anthropometric standard widely used to evaluate variations in height and its distribution. The height data sample is from a comprehensive global project, initially organised and published by Baten and Blum (2011), with an extension by Radatz & Baten (2025). This dataset is publicly accessible through the Clio Infra website and was recently expanded in 2024 (Baten et al., 2024). Height and height inequality data at the country level are collected from various sources, including early

[16] Evidence shows that population average heights are far less driven by genetic factors; for example, during a period of severe protein deficiency in mid-19th-century Holland, Dutch people were very short by European standards, whereas today they are often regarded as among the tallest in the world (Baten and Blum, 2012). While early 20th-century anthropologists attributed many size patterns (e.g., tall Tutsi and Masai) to genetics, later research identified these growth patterns as mainly resulting from dietary quality and a healthy environment (Bogin, 2020).

national surveys and international household surveys like the Demographic and Health Surveys (DHS), especially for developing countries and more recent years. The extensive data collection yields Height-Gini indexes for 193 countries spanning birth decades from 1810 to 2000. Each decade reflects the height inequality among people born during that period, with each spanning 10 years. For example, the 1990 decade includes individuals born between 1990 and 1999.

The Gini Coefficient is typically used to measure income inequality. However, before the 1980s, there was little evidence on income inequality in many developing countries. Recent studies have instead used the coefficient of variation (CV) of height as a proxy indicator, or the Height-Gini coefficient, which can be derived from the CV itself by following a consolidated procedure exposed in Baten (1999), Baten and Blum (2011), Moradi and Baten (2005), and Baten and Mumme (2013). If average stature is an indicator of average dietary quality and health, inequalities in health can be measured using the height coefficient of variation or the Gini index for a population within a given birth decade. Baten (1999, 2000b) argues that the CV is also a good indicator of income inequality within society (see also Moradi and Baten, 2005; van Zanden et al., 2014). The two measures are correlated with the distribution of nutrition and standards of living. To understand the influence of inequality on height, we compare outcomes of a hypothetical situation, where a population is subject to the alternative distribution of resources, (A) and (B), after birth (Moradi & Baten 2005):

A. Every individual is endowed with the same amount and quality of resources (e.g., nutrition and health services). This setting constitutes a condition of perfect equality.
B. The resources are unequally distributed, yet independent of the genetics of an individual.

Case (A) reflects the biological variance in a normally distributed stature since the size distribution should only reflect genetics. However, as inequality increases from (A) to (B), some people benefit and grow taller, while others grow smaller as they endure poor nutrition and low standards of living. As a result, when compared to the scenario of perfect equality, the richer income groups' height shifts to the right, while the poorer ones shift to the left. Therefore, increasing resource inequality will result in greater height inequality. If resource endowments differ greatly between groups, it may even result in a bimodal size distribution. Even though biological variance still accounts for a large proportion of total variance, most size distributions tend towards normality, albeit with a larger standard deviation than in theory (A).

Finally, because biological variance increases with average stature, the standard deviation alone lacks temporal comparability as a measure of inequality (Schmitt and Harrison, 1988). This effect is accounted for by the CV, which is divided by the average height, making it a more reliable and consistent measure of height inequality. Our data contain ten-year birth-decade t and country i observations, averaged for the adult population (22 to 50 years old), where the CV is defined as follows:

$$CV_{it} = \frac{\sigma_{it}}{\mu_{it}} \times 100 \tag{6}$$

Baten (1999, 2000a) uses the CV measure to compare size differences across social groups in Bavaria, southern Germany, in the early 19th century. Moradi and Baten (2005) transform the CV values into Gini coefficients of the Height distribution (Height-Gini), which has already been widely used as an inequality indicator in empirical studies (Blum, 2014; van Zanden et al., 2014; Baten et al., 2024), and which we are using here as well. This final step, namely the transformation of the CV index into a Height-Gini, is motivated by the fact that the Gini units are easier to read and interpret. This measure has been used by Baten et al. (2024) to assess the impact of universal health insurance expansions on health inequality across 134 countries over nearly two centuries. To address potential outliers in height inequality, we first examined its distribution using boxplots. This visual inspection revealed the presence of extreme values that could significantly bias our estimation results. We applied the winsorization method at the 1st and 99th percentiles to address outliers in height inequality.

E.3.3 Treatment Variable

The treatment variable is exposure to CE. CE refers to a legally required period of education, defined as the number of years, age range, or both, for children and young people (UNESCO, n.d). It is a legal imposition, usually governed by national law, that defines the exact period during which free and compulsory education should last. It could also be defined as the number of years a child is expected to attend school, or, more generally, to receive instruction in any form. The duration of such a period varies from country to country, depending on each country's history, political will, social needs, and resources. In the analysis, we focus on the first universal CE imposition, in which a legal requirement for CE applies to all children in the relevant age group, regardless of population group (e.g., gender, ethnicity, or geographic region) (Del Río, 2025). This distinction is critical, as partial enforcement or selective application of education laws often reflects deeper structural inequalities rather than genuine educational reform (Ansell, 2010).

Cohorts are considered fully treated if their schooling occurred entirely under the policy, or if it overlapped with the policy[17]. We define the treatment based on both the cohort's age at school entry and the duration of schooling relative to the policy decade. The policy definition year is defined as follows: if a country enacted and passed a law in 1975, it is coded as 1 for the adoption of CE in 1975 and the decade of 1970-79. This analysis excludes consideration of actual implementation and any further reforms or, less frequently, abolitions. These policy changes, observed in countries such as Afghanistan and Azerbaijan, were not incorporated into the analysis due to insufficient data on height inequality for the study period.

For regions without independent geographic boundaries, the coding is based on their status as territories within larger political entities at the time of policy adoption. For example, when CE was implemented across the Soviet Union in the 1930s, this policy applied to all the constituent republics; therefore, the same policy year was adopted for Armenia,

[17] Cohorts are exposed to CE if they were born in or after the decade of CE implementation or if their schooling period overlapped with it.

Kazakhstan, Kyrgyzstan, Lithuania, Russia, Tajikistan, Turkmenistan, and Uzbekistan. The data on education policies and systems, including CE, is sourced from Del Río et al. (2025), who provide a comprehensive global dataset on historical education regulations. Table E.9 in the appendix shows the years of adoption of compulsory schooling without exclusions. The earliest adoptions occurred in Europe and the Americas, and the later ones mainly in Africa and Asia. The analysis focused on 62 countries that exhibited variation in compulsory schooling exposure across birth cohorts. Countries that had already implemented CE policies before the observation period were excluded as they lacked pre-policy baseline data. An additional 7 countries without CE implementation during the study period were included in robustness checks as comparison groups.

E.3.4 Control Variables

The control variables in the study are country-level aggregate measures. We expected the following signs keeping in mind that a higher Height-Gini means higher health inequality: (i) a country's population (+), (ii) civil wars onset (+), (iii) Universal Health Coverage (-), (iv) land inequality (+), (v) ethnic fractionalisation (+); (vi) teacher training (-), (vii) the degree of urbanisation (+/-) and presence of a department of education(-). These are included because deeper social, economic, and political factors may simultaneously influence both the introduction of CE and trends in health inequality. Economic growth, public health interventions, political institutions, religion, social stratification, and cultural norms could have shaped both CE adoption and health improvements (Acemoglu et al., 2001; Becker & Woessmann, 2009; Bleakley, 2010; Costa & Steckel, 1997; Cutler et al., 2006; Galor & Moav, 2002).

The expected sign for the population variable is motivated by the observation that a larger population may imply greater diversity in health and nutrition across different regions of the country, potentially contributing to greater height inequality (Akachi & Canning, 2010; Eveleth & Tanner, 1976). Civil wars can disrupt healthcare, education, and nutrition systems, leading to worsened health outcomes and exacerbating height inequality (Akresh et al., 2012; Bundervoet et al., 2009; Gates et al., 2012). Universal Health Coverage improves access to healthcare, reducing disparities in health outcomes and promoting more equal growth conditions, thus reducing height inequality (Baten et al., 2024; Moreno-Serra & Smith, 2012).

Higher land inequality often leads to unequal access to resources like food and nutrition, which can result in disparities in growth and contribute to height inequality (Vollmer & Ziegler, 2009). High ethnic fractionalisation can result in social fragmentation and unequal access to healthcare, education, and economic opportunities, exacerbating height inequality across different groups (Alesina et al., 1999; Easterly & Levine, 1997). The years of schooling for CE control for the quantity of education as more years would imply more exposure to education and thus potentially is nowadays typically associated with hospitals in the neighbourhood, as well as better access to health care, leading to better health outcomes (Oreopoulos, 2006). Finally, increasing urbanisation typically provides better access to healthcare, nutrition, and sanitation, potentially reducing height inequality. On the other hand, in some development episodes, the rural-urban disparities might persist or even enlarge, which could lead to greater social and economic stratification within places, and hence increasing height inequality; for this reason we have no prior expectation, the sign could be positive or negative (Marmot, 2005; Montgomery & Hewett, 2005; Van de Poel et al., 2007). The availability and quality of teacher training are expected to reduce educational disparities, improve learning outcomes, and, indirectly, lower health inequality through better human capital formation. The existence of an institutional body dedicated to education typically signals stronger governance and policy coordination, which should help reduce inequality in both education and health. All variables are defined in section E.8.1 in the appendix.

E.3.5 Statistical Analysis

E.3.5.1 Identification Strategy

Countries adopted CE policies at different points across the study period, creating a staggered treatment structure. Before applying staggered difference-in-differences estimators necessary to exploit such variations, we first estimate a baseline specification to establish whether CE is associated with height inequality, employing region-by-half-century fixed effects to identify effects on height inequality:

$$Y_{ct} = \alpha + \beta \mathrm{CE}_{ct} + \gamma_{rh} + \theta X_{ct} + \varepsilon_{ct} \tag{7}$$

where Y_{ct} represents the height inequality for country c at decade t, measured using the Gini coefficient of height by country-decade cohorts; CE_{ct} is an indicator equal to one if country cohort c schooling period overlapped with or followed the country's adoption of CE, and zero otherwise by decade t; γ_{rh} represents the full interaction of region and half-century fixed effects; X_{ct} is a vector of time-varying country-level controls; and ε_{ct} is the error term. The model is estimated using a high-dimensional fixed-effects estimator that absorbs region-by-half-century fixed effects via iterative projection (Correia, 2016). Inference relies on heteroskedasticity-robust standard errors (White, 1980), which account for arbitrary forms of heteroskedasticity in the error structure. The choice of region-by-half-century fixed effects, rather than the more standard two-way fixed effects (region and half-century separately, or country-by-decade fixed effects), was driven by empirical evidence.

Graphical evidence of regional trends in height inequality over time (Figure E.1) shows variation across regions. Further, the specification controls broad, time-varying structural and historical differences across clusters of countries, consistent with Durlauf et al. (2005), and is appropriate given the slow-moving nature of height inequality. It controls for potential spillovers or diffusion effects within regional-temporal contexts. Educational policies often diffuse across neighbouring countries or countries with similar characteristics during the same historical period (Benavot & Riddle, 1988). If early adopters of compulsory schooling within a region influenced inequality trajectories in late-adopting countries through demonstration effects, labour market integration, or cultural diffusion, then comparing across regions and time periods might conflate direct treatment effects with indirect spillover effects. The region-by-half-century fixed effects absorb these region-specific spillovers, isolating the direct effect of a country's own adoption decision.

E.3.5.2 Staggered Difference-In-Difference (DiD) Analysis

Event Analysis

To assess the prerequisite for using the staggered DiD approach, we test for parallel trends, assuming that, in the absence of CE policies, exposed and unexposed cohorts would have experienced similar trends in height inequality. This event study regression estimates how the effect of CE adoption changes over time. Importantly, the coefficients on pre-treatment periods (leads) test the parallel trends assumption: if statistically insignificant, they support the assumption that trends were parallel before treatment. The decade immediately before the CE adoption (time = - 10) serves as the baseline period, following standard practice in event studies (Clarke & Tapia-Schythe, 2021; Sun & Abraham, 2021). We use the event analysis in this study to conduct the parallel trend test using the following model:

$$Y_{it} = \gamma_i + \sum_{q=-Q}^{t} \beta_q D_{qi} + \gamma\ Controls_{it} + \theta_i + \mu_t + \varepsilon_{qit} \tag{8}$$

where D_{qi} indicates the qth decade before and after whether country i adopted compulsory schooling. We examine the pre- and post-trends of the CE over a timeline covering three decades before and four decades after its implementation. The four post-implementation decades allow us to capture both immediate effects and longer-term impacts of CE policies on height inequality, as nutritional and health improvements from educational exposure may take time to fully manifest in physical development outcomes (Arntsen et al., 2023; Maurer, 2010; Silventoinen et al., 2000b).

Evidence suggests that intergenerational effects of education reforms often become more pronounced over multiple decades (Lundborg et al., 2014). Regarding the pre-treatment period, we include three decades as leads to test for pre-existing trends that could confound our results (Roth, 2022; Sun & Abraham, 2021). Such a pre-treatment time frame gives us enough time to spot any patterns that may have existed before the policy was implemented, while avoiding the inclusion of distant pre-periods that may reflect trends unrelated to our treatment (Schmidheiny & Siegloch, 2023).

Because CE policies were adopted at different times across countries, we complement our baseline estimation strategy with staggered difference-in-differences methods (Callaway & Sant'Anna, 2021), which account for treatment timing heterogeneity (Goodman-Bacon, 2021). To exploit the staggered nature of our treatment, we implement two alternative estimators specifically developed for staggered difference-in-differences designs: the Gardner (2022) two-stage estimator and the Callaway and Sant'Anna (2021) estimator. We begin estimation with the Gardner (2022) estimator, which remains valid under heterogeneous treatment effects. It is estimated in two stages.

We first regress the outcome on region fixed effects, half-century fixed effects, and observed covariates and then obtain the residualised outcomes to remove the influence of time-invariant cohort characteristics, time shocks, and observed controls, ensuring that the second-stage regression does not contaminate event-time coefficients with FE estimation error. In the second step, we regress the residualised outcome on the set of event-time indicators. To obtain coefficients tracing the dynamic effects of exposure to CE.

To complement the Gardner (2022) estimator, we also implement the Callaway and Sant'Anna (2021) difference-in-differences estimator (C&SDiD), which identifies cohort-specific treatment effects under staggered adoption. The C&SDiD constructs valid counterfactuals using only never-treated or not-yet-treated countries, thereby addressing the contamination and weighting issues inherent in standard two-way fixed-effects models. Moreover, the Callaway and Sant'Anna estimator is particularly valuable in our context because it allows treatment effects to vary flexibly across adoption cohorts and does not rely on restrictive homogeneous-effects assumptions. It therefore provides a complementary perspective to the Gardner (2022) estimator: while Gardner identifies cohort-invariant dynamic effects, the C&S approach identifies cohort-specific effects using only valid comparisons. Together, these two methods offer a comprehensive and robust assessment of the dynamic and distributional impact of CE on height inequality.

E.3.5.3 Robustness tests

To assess the validity of the identification strategy, we conducted different robustness checks. First, we estimated a placebo test by assigning a hypothetical policy reform five decades before the actual reform. We chose five decades to allow for sufficient temporal separation from the actual policy reform and to minimise the risk of capturing early signals or indirect effects of the actual reform. A non-significant coefficient would indicate that CE Introduction reduced height inequality and the observed effects were not driven by pre-existing trends. Otherwise, our conclusions would not be robust. To assess whether the effect of CE on health inequality varies across contexts, a heterogeneity analysis was conducted.

We examined these potential sources of variation: colonial history, timing of adoption and world region. First, we classified countries according to their colonial past to test whether institutional legacies affected the relationship between education and health inequality. According to Acemoglu et al. (2001), the type of colonial legacy (whether a country was a colony or a colonialist) has long-lasting impacts on the development of institutions and economic structures, which in turn can influence social outcomes such as education and height inequality. Countries with colonial legacies often exhibit persistent disparities in educational quality, healthcare infrastructure, and governance mechanisms, which can fundamentally shape how compulsory schooling reforms translate into health benefits across different socio-economic strata (Cogneau & Moradi, 2014).

To account for this historical dimension, we incorporate colonial status as a moderating variable in the analysis. This is because the CE effect on height inequality might operate differently across formerly colonised nations versus those that were colonisers, as well as those without significant colonial histories. In the analysis, we classify countries as colonies, whether settlement or extraction colonies and non-colonised countries. Regional classification captures broad contextual differences in economic development, health infrastructure, baseline levels of inequality and educational capacity (Mackenbach, 2006). Regional variation in the implementation and enforcement of CE policies, alongside divergent returns to education in labour markets, may further contribute to heterogeneous effects on health inequality (Brunello et al., 2016). We also analysed the effect of the timing of policy adoption, based on the median adoption time of 1910. We want to assess whether the effects of CE on height inequality differ between early and late adopters. Next, we examine whether the effects of compulsory schooling on height inequality vary geographically. We estimate the effect accounting for region-specific treatment effects.

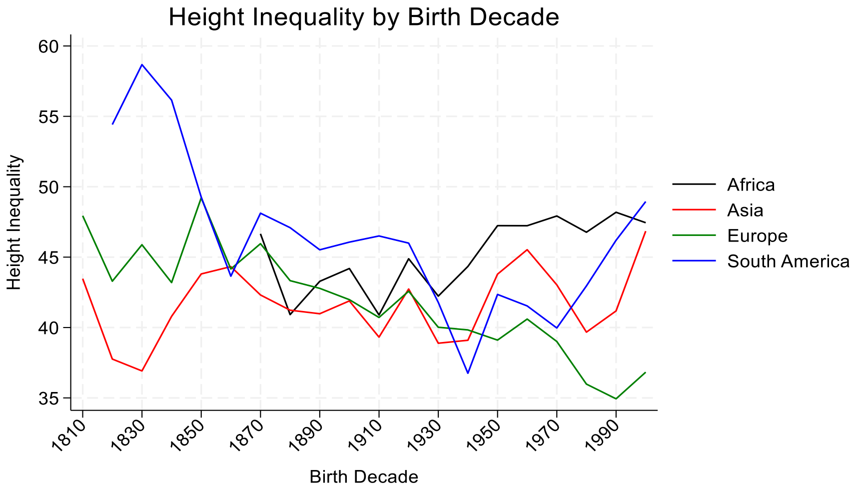
E.4 Results

The introduction of CE across countries occurred gradually between 1810 and 2010. The earliest adoptions occurred in Europe during the 18th century, while the latest occurred in Africa during the 1900s and 2000s. We utilise data from an unbalanced panel of 62 countries observed over 18 decadal periods from 1810 to 2000. Our sample includes only countries with at least 5 decades of height inequality data to ensure a comprehensive view of variation (see Table E.9 for included countries). As noted earlier, countries that adopted CE before 1810 were excluded from the regression analysis; therefore, the analytic sample consists only of country-decade observations in which at least one cohort was exposed to compulsory schooling. As previously noted, the CE policies considered are those in which schooling laws were enacted without explicit restrictions on enforcement, region, gender, or social group.

E.4.1 Height Inequality

Regional trends in Figure E.1 reveal pronounced heterogeneity in height inequality. South America exhibits the most dramatic fluctuations, with the highest height inequality for cohorts born in the early 19th century, especially around the 1830s, before gradually declining through the mid-20th century, before rising again toward the end of the century. The European region generally shows a downward trend starting with moderate inequality in the early 1800s that fluctuated but ultimately declined more steadily after 1900, reaching the lowest levels among the four regions by the late 20th century. Africa shows greater variability, with no clear long-term trend until the mid-1900s, when inequality began to increase, making it the continent with the highest height inequality from the 1950s to 2000. Asia experienced lower height inequality for early birth cohorts, saw an increase toward the late 19th century, a dip for individuals born around the 1930s and 1940s, and a rise again for those born after 1950, though it shows some increase in the late 1900s.

Figure E.1: Height Inequality Distribution



Notes: The graph shows average height inequality by birth decade across world regions. Sample spans birth decades from 1810 to 2000. The analysis for Africa begins at 1870, as there are fewer countries with data before 1870. Height inequality is measured as the Gini coefficient of adult heights.

E.4.2 Summary Statistics

Table E.1 reports the descriptive statistics of our sample. On average, the height inequality is 43.4 with a considerable variation of 7.40. However, the minimum value is 25, while the maximum is 81.33, suggesting that some countries exhibited significantly greater height-disparity than others. About 55 per cent of the country-decade observations have been exposed to CE policies. There are substantial differences in urban population in the study, with the average at 27 per cent and the ethnic diversity at 0.41, with a maximum of 0.93, indicating that some countries are highly ethnically diverse.

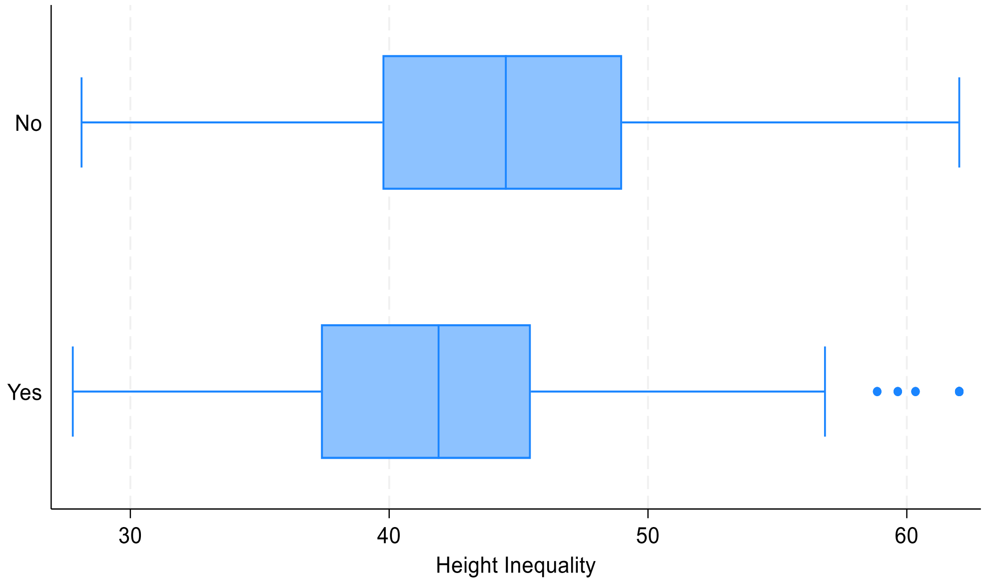
Table E.1: Descriptive Statistics

Variables	n	Mean	Std. Dev.	min	max
Height Inequality	701	43.41	7.40	25	81.33
Exposure to CE	701	0.55	0.49	0	1
Urbanisation	701	0.27	0.21	0.001	0.90
Civil War Onset	701	0.13	0.33	0	1
Universal Health Coverage	701	0.20	0.40	0	1
Land Inequality	606	61.30	14.04	30.70	93.19
Ethnic fractionalisation	681	0.41	0.27	0.002	0.93
Population (millions)	700	42.10	124	0.16	1260
Teacher Training	591	0.94	0.24	0	1
Education Department Presence	591	0.79	0.40	0	1

Notes: All variables are measured at the country-decade level.

Figure E.2 shows the distribution of height inequality by exposure to compulsory schooling. Country-decade cohorts exposed to compulsory schooling exhibit lower height inequality than those not exposed. The maximum height inequality is also much higher in the unexposed group than in the exposed group.

Figure E.2: Height Inequality by Compulsory Schooling Status



E.4.3 Regression Estimates

Our baseline specifications in Table E.2 (Column 1-3, 5) reveal that countries that implemented compulsory education laws experienced significant reductions in height inequality. Among control variables, urbanisation consistently predicts higher inequality, while universal health coverage reduces height inequality. Land inequality positively predicts height inequality. Columns 2 to 5 reveal that teacher training and the existence of education departments individually lead to higher height inequality, yet their interaction is significantly negative. This result suggests that it is likely that during early educational expansion, teacher training and existence of education departments initially benefited privileged populations, though their joint presence created pressures toward broader access and hence a reduction in inequality. The three-way interaction in Column 4 reveals critical heterogeneity in CE's effectiveness. The positive three-way interaction indicates that CE was substantially less effective at reducing inequality in countries that had developed both teacher training and existing education departments. This suggests that the CE effect was smaller where educational infrastructure was most developed. However, population size and civil wars do not predict height inequality. Finally, we consider a specification (5) without the North American region, and it yields comparable estimates.

Table E.2: Baseline Regression Results

DV: Height Inequality	(1)	(2)	(3)	(4)	(5)
CE Exposure	-1.439**	-1.555**	-1.480**	-2.225	-1.387*
	(0.659)	(0.728)	(0.722)	(2.388)	(0.710)
Teacher Training		1.250	3.380***	3.606**	4.453***
		(1.246)	(1.180)	(1.446)	(1.158)
Education Department		1.053	6.985***	8.927***	6.554**
		(0.942)	(2.666)	(3.252)	(2.689)
Teacher Training × Education Department			-6.621**	-9.374***	-7.971***
			(2.700)	(3.290)	(2.710)
CE × Teacher Training				-1.097	
				(2.513)	
CE × Education Department				-7.067	
				(4.390)	
CE × Teacher × Education Department				9.300**	
				(4.468)	
Urbanisation (log)	1.067**	1.202***	1.134**	1.112**	1.259***
	(0.421)	(0.441)	(0.440)	(0.453)	(0.438)
Civil War	1.143	1.093	1.118	1.172	0.920
	(0.948)	(0.931)	(0.931)	(0.929)	(0.963)
Universal Health Coverage	-4.049***	-4.006***	-4.018***	-4.088***	-2.845***
	(0.917)	(1.002)	(1.003)	(1.030)	(0.972)
Land Inequality (Gini)	0.112***	0.119***	0.118***	0.120***	0.110***
	(0.022)	(0.026)	(0.026)	(0.026)	(0.027)
Ethnic Fractionalization	0.820	3.058**	3.008**	3.778**	3.812**
	(1.470)	(1.514)	(1.497)	(1.663)	(1.497)
Population (log)	-0.110	-0.285	-0.219	-0.225	-0.160
	(0.227)	(0.261)	(0.258)	(0.259)	(0.259)
Observations	600	522	522	522	494
R-squared	0.301	0.351	0.361	0.367	0.370

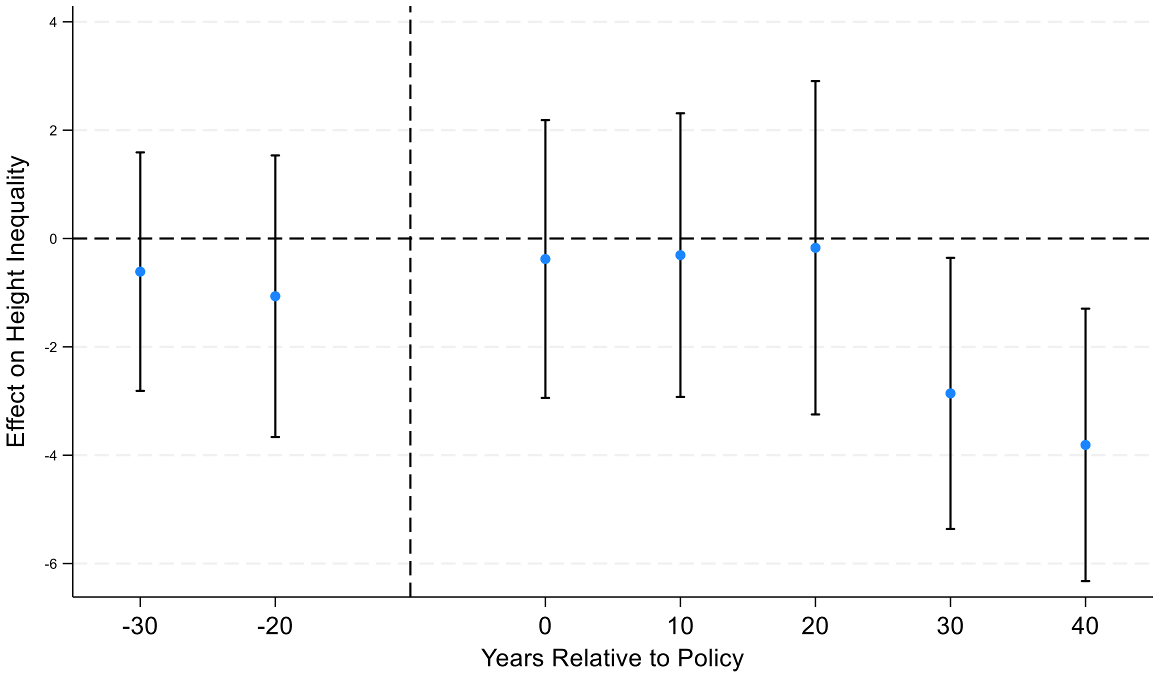
Notes: Robust Standard errors in parentheses. Dependent variable: Height inequality (Gini coefficient). All specifications include region×half-century fixed effects. ***, **, * significant at the 1, 5, and 10%-level respectively.

E.4.4 Event Analysis and Pre-treatment Dynamics

To verify the DiD assumptions, we analyse pre-trends in the event study for cohorts born up to 3 decades before and 4 decades after policy implementation. As shown in Figure

E.3, the estimates before the policy reveal no significant effect, supporting the assumption of parallel trends before the start of compulsory schooling. Following policy implementation, we observe modest reductions in height inequality that are not statistically significant for the immediate post-treatment period (0 to 20 years). The effects become larger and significant in later periods, 30 and 40 years post-policy. This suggests that CE effects on height inequality emerge gradually, as cohorts exposed to mandatory schooling reach adulthood. Therefore, exposure to CE reduces height inequality over time.

Figure E.3: Event-Study Analysis



Notes: Graph shows event study coefficients and 95% confidence intervals from the regression of height inequality on time-to-event dummies. Time 0 represents CE adoption. The base period is 1 decade before the introduction. Analysis covers 3 decades pre- and 4 decades post-introduction. Standard errors clustered at the country level

Further, a formal test of the joint significance of the pre-treatment coefficients indicates no statistically significant pre-trend ($F=0.32$, $Prob > F = 0.723$), consistent with parallel trends.

E.4.5 Difference-in-Difference Analysis

As highlighted in the methods section, we address recent concerns about potential biases in two-way fixed effects estimators when treatment timing varies and effects are heterogeneous across units or time periods (Goodman-Bacon 2021; Sun and Abraham 2021) by re-estimating our main specification using two difference-in-differences estimators specifically designed for staggered adoption settings: the Gardner (2022) two-stage DiD estimator and the Callaway and Sant'Anna (2021) estimator. The Two-Stage Difference-in-Differences by Gardner (2022) is a Two-Way Fixed Effect model for height inequality, controlling for baseline differences across cohorts, regions, and time periods. This approach is robust to treatment-effect heterogeneity when treatment adoption is staggered. At the first stage, we include covariates that may predict CE exposure, including regional and time FE, as well as all other covariates. The second stage regresses height inequality on the predicted values of the DiD treatment variable, with standard errors clustered by country.

The Callaway-Sant'Anna (2021) estimator estimates group-time-specific treatment effects and aggregates them into an overall Average Treatment Effect on the Treated (ATT), avoiding comparisons between already-treated and newly treated units that can bias two way fixed effects estimates. We implement this estimator with two control group specifications. Our primary specification uses not-yet-treated country cohorts as controls, comparing early adopters to late adopters before the latter implement policies. This provides a larger, more stable control group and ensures comparisons between countries that all eventually adopted compulsory education. As a robustness check, we also estimate the model using never-treated countries as controls, though we use a simpler regression-based method rather than the more efficient doubly robust IPW approach due to the small sample size. The results are shown in Table E.3.

Table E.3: 2-stage Difference-in-Difference

	2-Stage DiD			Callaway+ Sant'Anna	
DiD	(1)	(2)	(3)	(4)[a]	(5)[b]
ATT	-2.55**	-2.82**	-2.59*	-6.11*	-1.98
	(1.22)	(1.42)	(1.33)	(3.13)	(2.18)
Controls	N	Y	Y		Y
Observations	701	509	522	239	173
Time + Region FE	Y	Y	Y	Y	Y

Notes: standard errors clustered at country level in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively. Column 3 includes the never-treated countries in the model. [a]CSDiD with not yet treated as controls, [b]CSDiD never treated as controls. Country and decade fixed effects included. ATT is the Average Treatment Effect on the Treated.

These results demonstrate that CE policies reduced height inequality across multiple DiD specifications with consistent negative coefficients. The 2-stage DiD estimates in columns (1) through (3) remain statistically significant and stable whether control variables are included or not. The Callaway-Sant'Anna estimator in column (4) shows a substantially larger negative effect, though it relies on fewer observations.

E.4.6 Mechanism Analysis

We examine a set of mechanisms through which the introduction of CE reduces height inequality. We identify three main mechanisms: First, we hypothesise that exposure to education increases access to education. As education levels rise, populations may demand more redistributive policies, such as public health investments and social safety nets, which improve childhood nutrition and healthcare access (Acemoglu & Robinson, 2012), reducing height inequality. Secondly, we argue that compulsory schooling can reduce height inequality through its effects on child mortality. With schooling, children and their families gain better knowledge of nutrition, hygiene, and health practices, which lowers the risk of early-life illness and death. Reduced child mortality enables more children to survive and reach their genetic growth potential, thereby decreasing extreme height variation within cohorts. Regions or groups with higher exposure to compulsory schooling often experience larger declines in child mortality, leading to a more uniform distribution of growth outcomes and narrower height gaps.

Education improves health literacy, nutrition, and access to healthcare, all of which are critical determinants of physical growth and height (Bozzoli et al., 2008). Third, we examine whether democracy may mediate the relationship between CE and height inequality. Education fosters civic participation and strengthens democratic institutions (Glaeser et al., 2007; Friedman et al., 2016), which in turn promote more equitable health outcomes through improved public service delivery, social safety nets, and healthcare access (Besley & Kudamatsu, 2006). This pathway is particularly relevant for height inequality because democratic accountability tends to redirect resources toward disadvantaged populations whose growth is most constrained by nutritional deprivation (Kudamatsu 2012). We used the mediating effect model to examine these mechanisms. We used the mechanism indicator first as the explained variable to test the effect of CE, and then we added the mechanism indicator into the model, as seen in Table E.4 below.

Table E.4: Mechanism Analysis Examining how Compulsory Education affects Height Inequality

Variables	(1) Average years of schooling (log)	(2) Height inequality	(3) Child mortality (log)	(4) Height inequality	(3) Democracy	(4) Height inequality
Average years of schooling (log)		-1.19**				
		(0.47)				
Child mortality (log)				1.01**		
				(0.47)		
Democracy[2]						0.61
						(1.05)
CE Exposure	0.26***	-0.33	-0.38***	-1.13	0.05	-1.94**
	(0.08)	(0.94)	(0.06)	(0.83)	(0.04)	(0.76)
Urbanisation (log)	0.22***	0.77	-0.24***	1.37***	0.04	2.28***
	(0.06)	(0.51)	(0.04)	(0.46)	(0.03)	(0.56)
Civil War Onset	-0.05	1.01	0.19***	0.92	-0.08	1.44
	(0.10)	(1.04)	(0.07)	(0.94)	(0.05)	(0.97)
Universal Health Coverage	0.18**	-3.33***	-0.37***	-3.64***	0.03	-4.34***
	(0.07)	(1.05)	(0.12)	(0.96)	(0.06)	(1.04)
Land Inequality	-0.00	0.12***	0.01**	0.11***	-0.00	0.13***
	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)	(0.03)
Ethnic fractionalisation	0.12	5.31***	-0.10	3.11**	0.23***	1.84
	(0.19)	(1.77)	(0.14)	(1.53)	(0.08)	(1.74)
Population (log)	-0.01	-0.61*	0.02	-0.24	-0.01	-0.27
	(0.03)	(0.32)	(0.02)	(0.26)	(0.01)	(0.27)
Teacher training	-0.07	1.40	0.05	3.33***	-0.13	1.66
	(0.23)	(1.30)	(0.08)	(1.17)	(0.08)	(1.47)
Department presence	0.43	7.56	0.17	6.81**	-0.06	3.35*
	(0.35)	(5.01)	(0.11)	(2.67)	(0.11)	(2.03)
Teacher training* Department presence	-0.21	-6.12	-0.09	-6.53**	-0.02	-2.93
	(0.37)	(5.01)	(0.12)	(2.70)	(0.12)	(2.23)
Observations	339	339	499	499	425	425
Adjusted R-squared	0.76	0.28	0.82	0.34	0.35	0.38
Time* Region FE	Y	Y	Y	Y	Y	Y

Note: This table shows the results of mechanism analysis. Columns (1, 2) present the result of Average years of schooling, columns (3, 4) present the result of Child mortality, and columns (5, 6) present the result of democracy. Robust standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

CE reduces height inequality primarily through its effects on education and child mortality. We found that CE laws were significantly associated with increased average years of schooling, and these additional years were associated with reduced height inequality, as shown in Table E.4. This aligns with historical evidence showing that CE catalysed human capital formation and social mobility in industrialised nations (Goldin & Katz, 2008). For child mortality, CE exposure significantly reduced child mortality. The positive coefficient on child mortality indicates that higher mortality is associated with greater height inequality. Therefore, by reducing mortality, CE indirectly reduces height inequality. The direct effect of CE on height inequality is not significant, suggesting that these mechanisms are channels through which CE affects height inequality. CE exposure shows no significant relationship with democratisation, and democracy itself has no significant association with height inequality. Therefore, CE policies reduce height inequality through expanding educational attainment and lowering child mortality rates.

E.5 Robustness Checks

Further, in this section, we examined the robustness of our estimates using placebo tests, heterogeneity analysis, quantile regression and ordered probit regression.

E.5.1 Placebo Tests and Heterogeneity Analysis

Table E.5 shows that the placebo variable's coefficient is not significant, indicating that our identification strategy is valid and that the results are due to the policy itself. Therefore, our results are not driven by pre-existing trends. However, the treatment CE effects diverge sharply when distinguishing between early and late adopters: countries implementing compulsory education before 1910 experienced significant reductions in height inequality, while late adopters show no significant effect. This suggests that sufficient time must elapse before distributional benefits materialise. The colonial history analysis further explains this heterogeneity: former colonies exhibit no significant CE effect, whereas non-colonised countries demonstrate inequality reductions. This could highlight differences in state capacity, institutional quality, or the extent to which education systems served egalitarian versus extractive purposes.

Regional patterns in column (6) indicate that Europe (-2.58) and South America (-6.43) drove the aggregate inequality reductions, while Africa (0.49) and Asia (0.32) show no effects, potentially reflecting regional differences in educational infrastructure, enforcement capacity, or complementary health investments. Across all specifications, the interaction between teacher training and departmental presence remains negative and often significant, strengthening earlier findings that administrative capacity with comprehensive teacher training systems produces the strongest inequality-reducing effects. However, this appears most pronounced among late adopters and in specific regional contexts. These results show that while the existence of compulsory schooling laws reflects state commitment to education, the extent of enforcement varies widely. In many African countries, for example, formal laws coexist with informal barriers such as school fees, child labour requirements, and gendered social norms (Basu & Van, 1998; UNESCO, 2022). This pattern highlights the gap between legal frameworks and practical implementation. Children from rural and low-income households often remain excluded despite the legal requirement, reinforcing the notion that de jure education rights must be supported by de facto accessibility measures (Acemoglu & Robinson, 2012).

Table E.5: Results of the Placebo Test and Heterogeneity Analysis

DV: Height Inequality	**(1) Placebo**	**(2) Early Adopter**	**(3) Late Adopter**	**(4) Colony**	**(5) Not Colonised**	**(6) Region Heterogeneity**
CE exposure	-1.71	-5.75***	0.78	2.82	-2.06**	
	(1.13)	(1.34)	(0.95)	(1.87)	(0.89)	
CE exposure*Europe						-2.58***
						(0.99)
CE exposure*Africa						0.49
						(0.92)
CE exposure*Asia						0.32
						(1.19)
CE exposure*South America						-6.43***
						(1.40)
Urbanisation (log)	0.99**	3.46***	0.35	0.93	2.19***	
	(0.42)	(1.15)	(0.53)	(0.92)	(0.61)	
Civil War Onset	1.14	2.15	0.96	2.40	0.65	
	(0.95)	(1.60)	(1.20)	(3.92)	(0.98)	
Universal Health Coverage	-4.05***	-4.98***	-5.87***		-4.38***	
	(1.01)	(1.35)	(2.03)		(1.03)	
Land Inequality	0.12***	0.10*	0.14***	-0.04	0.13***	
	(0.03)	(0.06)	(0.03)	(0.06)	(0.03)	
Ethnic fractionalisation	3.08**	2.69	3.86**	11.20**	2.91*	
	(1.51)	(3.54)	(1.91)	(5.26)	(1.59)	
Population (log)	-0.24	0.54	-0.91***	0.81	-0.16	
	(0.26)	(0.52)	(0.33)	(0.88)	(0.28)	
Teacher training	3.79***	2.43	1.42	0.81	3.49**	
	(1.25)	(2.29)	(1.47)	(2.03)	(1.50)	
Department presence	6.98***	0.23	13.27***	27.56***	4.65**	
	(2.60)	(2.45)	(3.45)	(3.56)	(1.91)	
Teacher training* Department presence	-6.91**	1.37	-13.76***	-26.01***	-4.51**	
	(2.68)	(2.54)	(3.52)	(3.89)	(2.14)	
Observations	509	213	296	78	429	509
Adjusted R-squared	0.32	0.40	0.35	0.35	0.37	0.28
Time* Region FE	Y	Y	Y	Y	Y	Y

Notes: Robust standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively. The dependent variable is height inequality measured with the Gini-Index of inequality in every model. The placebo is assessed on the assumption that the CE reform was adopted 50 years earlier than the actual policy adoption. Late adoption is defined as adoption after the median year of adoption in the sample.

E.5.2 Quantile Regression

We employed quantile regression to capture the heterogeneous effects of CE across different points of the conditional distribution of height inequality. Unlike ordinary least squares (OLS) regression, which estimates relationships only at the conditional mean, quantile regression allows us to examine how the relationship between variables may vary at different quantiles of the height inequality (Koenker & Bassett, 1978). Quantile regression is more robust to outliers than traditional OLS regression because it handles skewed data better (Fournier & Koske, 2012; Garza-Rodriguez et al., 2021; Hung et al., 2010; Lee & Lee, 2006; Sotsha et al., 2019), and allows us to identify whether the treatment has different impacts at the lower tail (10th and 25th percentiles), median (50th percentile), or upper tail (75th and 90th percentiles) of the distribution of height inequality, better than the OLS regression that captures only the average effect.

We employed non-Winsorized height inequality values in the quantile regression analysis. This is because we want to preserve the complete distributional information about height inequality, which is essential for quantile regression's intended purpose of examining heterogeneous effects across its distribution of height inequality[18]. We include all the controls in the model as well as fixed effects for world regions and half-centuries. The results in Table E.6 in the appendix show that CE has a consistent negative relationship with height inequality across all model specifications, though not significant at all percentiles. CE is statistically significant at the 10th, 75th and 90th percentiles. There are stronger reductions at the top. This means that CE has effects concentrated among populations with the highest inequality; no significant effects are observed at the 25th or 50th percentiles. These results align with the literature that explains that CE has redistributive potential.

[18] We used the simultaneous quantile regression approach because it provides bootstrapped standard errors that are robust to heteroskedasticity and enables proper statistical comparison of coefficients across quantiles through a unified variance-covariance matrix (Cameron & Trivedi, 2009).

E.5.3 Ordered Probit Regression

We estimated the relationship between CE and height inequality using the ordered probit model. We transformed the height inequality into an ordered categorical variable with 4 levels, ranging from 1 (lowest inequality) to 4 (highest inequality). 1 is classified as very low, 2 is low, 3 is high, and 4 is very high. The results in Table E.7 indicate that CE reduces height inequality. The marginal effects of lower height inequality classified as very low is positive, revealing that CE increases the probability of being in the lower height inequality categories. The marginal effects of high and very high are negative, implying that CE decreases the likelihood of falling into higher inequality categories. This indicates that CE increases the probability of a population exhibiting lower levels of height inequality. The results are specifically indicative of exposure to CE increasing the probability of being in the lowest and second-lowest inequality categories. However, exposure to CE correspondingly reduces the likelihood of being in the two highest inequality categories. This result highlights that CE exposure reverses severe health disparities, a finding that directly parallels the quantile regression results showing negative effects of CE on height inequality.

E.5.4 Income-Policy Timing Deviations

The timing of compulsory schooling adoption correlates strongly with economic development, with wealthier nations typically implementing such policies earlier than their poorer counterparts (Benavot & Riddle, 1988). To test whether this pattern biases our results, we created a variable identifying countries that deviated from this expected relationship. This pattern raises concerns about potential confounding, as both educational policy adoption and height inequality may be driven by underlying economic conditions rather than representing a causal relationship. To address this concern, we constructed a variable identifying countries that deviated from the expected GDP-adoption timing relationship, specifically early adopters with relatively low GDP and late adopters with relatively high GDP. These deviations may reflect unique political, institutional, or cultural factors that influenced policy timing independent of economic capacity (Lindert, 2004; Murtin & Viarengo, 2011). Including this variable as a control in our regression specifications did not change the magnitude or significance of the effect of CE on height inequality, as seen in

Table E.8. The GDP timing results show no meaningful effect. Therefore, the effect of CE is not driven by richer countries adopting CE earlier or poorer countries adopting later.

E.6 Conclusion

We have studied the impact of two centuries of CE reforms on height inequality. We define CE as the existence of a legal requirement mandating schooling for all children in the relevant age group, and not limited to specific population groups such as gender, ethnicity, or region. CE reforms had notable effects, even from a historical viewpoint, with a country's levels of child mortality and years of schooling serving as strong mediators. Additionally, we find that the effect of CE varies widely across colonial histories and global locations, with some regions and countries that were not colonised experiencing a greater reduction in inequality. CE reduces height inequality, particularly among populations at the higher end of the distribution (75th and 90th percentiles). Marginal effects indicate that exposure to CE increases the likelihood of a population being in the lowest height-inequality groups, while decreasing the likelihood of being in the highest inequality groups. These findings remain consistent even when accounting for countries that deviate from typical GDP-policy adoption patterns. Our study emphasises the redistributive potential of CE in shaping long-term population health outcomes.

E.7 References

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E.8 Appendix

Table E.6: Quantile Regression Results

DV: Height inequality	10th	25th	50th	75th	90th
CE exposure	-1.344*	-0.745	-0.529	-2.810*	-6.393***
	(0.695)	(0.839)	(0.901)	(1.629)	(2.254)
Urbanisation	0.762	0.031	0.968*	1.323**	1.937**
	(0.754)	(0.597)	(0.572)	(0.520)	(0.849)
Civil War Onset	-0.312	0.759	0.700	1.977	2.723
	(1.366)	(1.068)	(1.448)	(2.207)	(2.117)
Universal Health Coverage	-3.111**	-2.721**	-3.986***	-1.789	-4.433**
	(1.431)	(1.268)	(1.163)	(1.705)	(2.185)
Land Inequality	0.010	0.096***	0.088**	0.122**	0.248***
	(0.035)	(0.035)	(0.037)	(0.055)	(0.045)
Ethnic fractionalisation	7.999***	5.720**	2.912	3.778	1.607
	(2.734)	(2.405)	(1.788)	(2.759)	(3.083)
Population (log)	0.519	0.124	-0.002	-0.440	-0.838*
	(0.492)	(0.379)	(0.355)	(0.396)	(0.445)
Teacher training	1.984	4.033**	1.954	4.310**	3.001
	(2.001)	(1.785)	(1.329)	(2.071)	(2.373)
Department presence	6.632**	7.613***	4.065	4.103	7.537
	(3.041)	(1.647)	(3.320)	(5.180)	(6.879)
Teacher training*Department	-5.215	-7.196***	-4.048	-3.969	-7.445
	(3.266)	(2.272)	(3.373)	(4.893)	(7.541)
Time*Region FE	Y	Y	Y	Y	Y

Notes: Observations=509; Standard errors in parentheses. The dependent variable is Height inequality. ***, **, * significant at the 1, 5, and 10%-level respectively.

Table E.7: Ordered Probit Regression Results

DV: Height inequality (Categorised)	Full model	ME (1)	ME (2)	ME (3)	ME (4)
CE exposure	-0.27*	0.06*	0.03	-0.02*	-0.07*
	(0.16)	(0.03)	(0.01)	(0.01)	(0.04)
Controls	Y	Y	Y	Y	Y
Observations	509	509	509	509	509
Wald chi2	803.72***				

Notes: Robust standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively. The dependent variable is height inequality categorised into 4. ME- Marginal effects.

Table E.8: Income-Policy Timing Deviations

DV: Height inequality	
CE Exposure	-1.24*
	(0.74)
Urbanisation (log)	1.38***
	(0.45)
Civil War Onset	1.86**
	(0.90)
Universal Health Coverage	-3.72***
	(0.90)
Land Inequality	0.07***
	(0.02)
Ethnic fractionalisation	5.89***
	(1.43)
Population (log)	0.15
	(0.25)
Teacher training	3.78***
	(1.13)
Department presence	5.68*
	(3.01)
Teacher training* Department presence	-5.81*
	(3.05)
High GDP early adopter	
Low GDP early adopter	-0.55
	(0.80)
High GDP late adopter	-0.91
	(0.85)
Observations	617
Adjusted R-squared	0.31
Time FE	Y

Notes: Robust standard errors in parentheses. ***, **, * significant at the 1, 5, and 10%-level respectively.

E.8.1 Data Sources and Variable Construction

Variable Construction & Sources

Height Inequality

Health inequality is proxied by height Gini, based on the distribution of heights within a country. Source: Baten and Blum (2012) available via the website of Clio Infra, and the extension done by Radatz & Baten (2024). Data source details can be found on the website of Clio Infra.

Compulsory Education

The treatment variable, captures the exposure to compulsory schooling, is defined based on the policy decade of implementation. Main Source: Del Río et al (2025).

Other Control Variables

- Population (log): The natural logarithm of a country's population at the start of each decade. Source: Fink-Jensen (2015), available via Clio Infra.
- Urbanisation: Degree of the urban population to the total population in a country for a specific decade. Source: Fink-Jensen (2015), available via Clio Infra.
- Universal Health Coverage: Defined as a dummy variable that takes on the value of one after the decade of the first legal implementation of health insurance, given that coverage for 90% of the population was achieved by 2010. Source: Baten et al. (2024).
- Land inequality: Measured as the Gini coefficient of plot sizes of estates. Source: Frankema (2010) and Baten and Juif (2014).
- Ethnic Fractionalization: Index of racial and linguistic characteristics to measure the ethnic fractionalization within a country. This is a time-invariant variable. Source: Alesina et al. (2003).
- Civil War onset: The variable is defined as a dummy variable with a value of 1 if a new civil war occurred in a country and decade, and zero if not. It is collected based on conflicts occurring within the national borders of countries. Data is from the Correlates of War Project (COW) using the most recent version on intra-state wars (v5.1), which covers the period from 1816 to 2014 (Palmer et al, 2020).
- Years of schooling: Defined as average years of schooling by country-decade. Source: Lee and Lee (2016), Barro and Lee (2013), and UNDP (2018).
- Height Growth: Indicates the growth of height from period t to period t + 1. Source: Baten and Blum (2015), available via Clio Infra.

- Democracy: Democracy is derived from the Polity5 project. It measures the degree of democratisation within a country. It ranges from -10 points for a full autocracy to $+10$ points for a fully consolidated democracy. Source: Marshall, M. G., & Gurr, T. R. (2020).
- Child mortality: Child mortality per 1000 live births. Source: Coppedge et al (2025)
- Teacher training: Presence of teacher training as a formal requirement- mandatory training to undergo before a person is allowed to teach at the primary or secondary school level (Yes/No). Source: Del Río et al. (2025).
- Department presence: Whether a country has a department of education at the national level. (Yes/No). Source: Del Río et al. (2025).

Table E.9: Compulsory Education Policy Years and Decades

Country	CE Policy year	Policy Decade	Decade Height Inequality
Algeria	1976	1970	1910-1930, 1950-1990
Argentina	1884	1880	1850-1920, 1950-2000
Armenia*	1918	1910	1850-1860, 1890-1910, 1990-2000
Bangladesh	2011	2010	1850-1880, 1950-2000
Burkina Faso	1996	1990	1910-1990
Canada	1916	1910	1820-1860, 1910-2000
Central African Republic	1997	1990	1940-1970, 1990
Chad	1960	1960	1870, 1920-1990
Chile	1920	1920	1820-1900, 1920-1990
China	1986	1980	1810-1920, 1940-2000
Croatia	1874	1950	1920-1930, 1950-1960, 1990-2000
Egypt	1923	1920	1880, 1900-2000
Estonia	1920	1920	1890-1920, 1950-2000
Finland	1921	1920	1880, 1900-1990
France	1882	1880	1810-2000
Gabon	1961	1960	1910-1920, 1970-1990
Georgia*	1918	1910	1890-1910, 1980-2000
Germany**	1919	1910	1810-1890, 1910-2000
Ghana	1961	1960	1810, 1830-1840, 1870-2000
Greece	1895	1890	1870-1880, 1920-1930, 1950-1990
India	1918	1910	1840-1890, 1910-2000
Indonesia	1989	1980	1840-1920, 1950-2000
Iran	1943	1940	1870-1890, 1910-1920, 1950-1980
Iraq	1976	1970	1880-1910, 1960-1990
Ireland	1892	1890	1810-1840, 1870, 1900-1920, 1950-2000
Israel	1949	1940	1920-1930, 1960-1990
Italy	1859	1850	1810-1820, 1880-1890, 1910-2000
Kazakhstan*	1918	1910	1890, 1910-1990
Kyrgyzstan*	1918	1910	1880-1990
Latvia	1930	1930	1880-1910, 1980-2000
Malawi	1994	1990	1870, 1910-1990
Mali	1962	1960	1920-2000
Mexico	1917	1910	1840-1920, 1950-2000
Morocco	1963	1960	1880, 1950-2000
Namibia	1990	1990	1880, 1920-1990
Netherlands	1901	1900	1810-1920, 1940-2000
Nigeria	2004	2000	1810-1820, 1890, 1960-2000
Norway	1842	1840	1820-1840, 1870, 1900-2000
Peru	1905	1900	1820-1880, 1910-1920, 1940-2000
Philippines	1988	1980	1870-1920, 1950-2000
Poland	1919	1910	1840-1890, 1920-2000
Portugal	1976	1970	1810-1920, 1950-1990
Republic of the Congo	1992	1990	1810, 1910-1990
Russia*	1918	1910	1850-1950, 1980-2000
Rwanda	1996	1990	1870, 1910-1920, 1950-1990

Table E.9: Continued

Country	CE Policy year	Policy Decade	Decade Height Inequality
Senegal	2004	2000	1810-1820, 1910-1920, 1940-1990
South Africa	1996	1990	1890-2000
South Korea	1953	1950	1890-1910, 1940-1990
Spain	1857	1850	1840-1880, 1950-2000
Sudan	1998	1990	1910-1930, 1960-1990
Sweden	1882	1880	1810-2000
Switzerland	1874	1870	1820-1830, 1870-1880, 1900-1920, 1940-2000
Tajikistan*	1918	1910	1870-1920, 1980-1990
Tanzania	1978	1970	1900-2000
Thailand	1921	1920	1900-1910, 1960-2000
Turkey	1923	1920	1860-1880, 1920-1930, 1950-2000
Turkmenistan*	1918	1910	1890, 1910-1920, 1980-2000
Uganda	1997	1990	1910-1920, 1950-1990
Ukraine	1924	1920	1820-1840, 1870-1880
United Kingdom	1880	1880	1810-2000
Uzbekistan*	1918	1910	1890-1920, 1940-1990
Zimbabwe	1987	1980	1900-1910, 1940-1990

Notes: *1918 as the adoption year, these countries were part of the Soviet Union; ** 1919 adopted because of the Weimar Constitution (the Constitution of the German Reich); The year of compulsory education adoption is defined as the first year in which a legal requirement mandating schooling for all children in the relevant age group was in place, and not cases where no such law existed or where the requirement applied only to certain groups of the population, such as by gender, ethnicity, or region.

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F Conclusion

This dissertation began with an observation: globally, some populations achieve long, healthy lives while others continue to face enduring disadvantages in health, development, and survival. The evidence presented across four empirical chapters demonstrates that health outcomes are profoundly shaped by human capital and institutions, which exert influence through both historical persistence and present-day mechanisms. In this dissertation, we found that patterns of elite numeracy in seventeenth to nineteenth-century Africa continue to influence contemporary malaria prevalence and life expectancy, that health literacy and numeracy independently shape disease-related behaviours, that institutional quality and development assistance are important for disease management, and that compulsory schooling policies reduce inequalities in physical development. Collectively, these findings establish that understanding health disparities requires moving beyond proximate explanations to examine the foundational conditions that determine how populations experience disease, deploy resources, and accumulate wellbeing across generations.

The first chapter established that historical human capital formation continues to shape contemporary health outcomes. Regions where elites possessed higher levels of numeracy during the seventeenth to the nineteenth century exhibit measurably lower malaria burden and higher life expectancy today, even after controlling for colonial experience, ecological conditions, and contemporary development indicators. This finding contributes to a growing body of evidence on the persistence of historical conditions, extending that literature into the domain of health outcomes and demonstrating that cognitive competencies among elites constitute an important dimension of long-run development trajectories.

The second chapter shifted focus from historical to contemporary human capital, examining how specific cognitive competencies shape health behaviours in a high-burden malaria area. The development of a context-appropriate measure of health literacy and health numeracy represented a necessary methodological step, recognising that instruments designed for high-income or other populations may not function equivalently in settings characterised by different disease profiles, healthcare systems, and educational backgrounds. The validated measures revealed that health literacy and numeracy have independent associations with malaria-related behaviours in Gabon, with numeracy showing powerful associations with treatment-seeking decisions and literacy with preventive measures. This disaggregation of cognitive competencies carries implications for intervention design. The findings suggest that effective health promotion requires attention to the specific cognitive demands placed on individuals and the distribution of relevant competencies within target populations. Simply providing information is insufficient; that information must be matched to the cognitive tools available to process and act upon it.

The third chapter examined the spatial dimensions of malaria control across 38 Sub-Saharan African countries, revealing that the disease burden, while declining overall, remains highly clustered geographically and shaped by institutional contexts. Contrary to expectations, higher health worker density, enhanced institutional effectiveness, and increased development assistance were associated with greater reported malaria burden, a pattern that persisted even after accounting for lagged effects. These findings suggest that better-functioning health systems may improve case detection and reporting. The geospatial analysis revealed that malaria burden is predominantly driven by local conditions, with limited spillover effects from neighbouring countries. This finding challenges assumptions about substantial cross-border transmission dynamics and suggests that within-country factors, including health system capacity, intervention coverage, and institutional quality, exert greater influence on disease outcomes than regional diffusion processes.

The fourth chapter provided comparative evidence on the effects of compulsory education policies on physical development, demonstrating that the policies reduced height inequality. These findings contribute to the literature on the causal effects of education by extending analysis beyond cognitive and economic outcomes to encompass anthropometric indicators that reflect cumulative health investments during childhood and adolescence. The reduction in height inequality is particularly noteworthy, suggesting that education policy can function as an equalising force by improving nutritional knowledge, enhancing household productivity, and increasing access to resources among disadvantaged populations. However, the magnitude of the effects and the pathways through which education influences growth differed, likely reflecting variation in baseline nutritional conditions, healthcare access, and the quality of schooling provided. These findings caution against assuming that education policies will generate uniform effects across contexts, while nonetheless establishing that investments in human capital formation yield dividends that extend well beyond labour-market outcomes to encompass fundamental dimensions of human wellbeing.

The findings of this dissertation carry several implications for policy approaches to improving population health. First, the persistence of historical determinants suggests that efforts to close contemporary health gaps must reckon with deep-rooted disparities that cannot be rapidly overcome through short-term interventions alone. Policymakers often operate with implicit assumptions of convergence, expecting that if appropriate interventions are implemented and sufficient resources allocated, health outcomes across populations will eventually equalise. The evidence presented here suggests such expectations may be overly optimistic. Societies disadvantaged by historical patterns of human capital formation face structural deficits that compound over time, affecting not only immediate health outcomes but also the capacity to absorb and effectively deploy resources for health improvements. Closing these gaps will require sustained commitment extending across decades, not merely election cycles or funding windows.

Second, development assistance for health effectiveness cannot be assessed without attention to institutional contexts and surveillance capacity; resource allocation to weak governance environments may generate limited measurable health gains regardless of intervention quality. Given that local country effects substantially exceed spillover effects, health systems strengthening within countries may yield greater returns than extensive regional coordination, though targeted cross-border collaboration remains important in border areas where both countries experience high transmission rates. The spatial clustering observed despite limited spillover effects indicates that geographical patterns likely reflect shared risk factors in neighbouring countries rather than direct cross-border transmission, suggesting that resources should be targeted to areas with similar geographical characteristics and high disease burden.

Third, the findings on health literacy and numeracy underscore the importance of tailoring health communication to the cognitive competencies present in target populations. Health promotion campaigns often assume literacy or numeracy levels that may not be widespread, leading to messages that fail to reach or influence intended audiences. Designing interventions that accommodate varying competencies through visual communication, simplified quantitative information, or peer education models may improve effectiveness. Moreover, investments in adult education focused specifically on health-related literacy and numeracy could yield health returns comparable to those of direct medical interventions, suggesting that education and health ministries should coordinate more closely than is typically the case.

Fourth, the effects of compulsory schooling policies on height inequality demonstrate that education policy constitutes a health intervention with benefits that extend beyond disease prevention or access to treatment. Schooling influences health through multiple pathways, including nutritional knowledge, household resource allocation, fertility decisions, and intergenerational transmission of health-promoting behaviours. These findings demonstrate that educational policies can have measurable effects on health inequality, suggesting that investments in human capital formation may yield health benefits that extend beyond traditional health interventions. While this research does not directly address resource allocation during health crises, it adds to a growing body of evidence that education represents an important pathway to improved population health outcomes with multiplier effects throughout society.

Finally, while the dissertation has examined multiple health outcomes, including malaria burden, life expectancy, and anthropometric indicators, as well as health behaviours, these represent only a subset of relevant health domains. The factors and mechanisms examined in this research likely extend to mental health, non-communicable disease burden, maternal and child health, and health system responsiveness, among other outcomes. Extending the analytical frameworks developed here to these domains would enrich understanding of how human capital and institutions shape the full spectrum of population health.

Health inequalities and variations are produced through social, economic, and political processes that determine who receives education, which societies build effective institutions, and how resources are distributed across populations and generations. The persistence of these inequalities reflects not merely the continuation of past injustices but the ongoing reproduction of systemic conditions that advantage some populations while disadvantaging others. Breaking these patterns requires understanding their origins and mechanisms, recognising that while contemporary health outcomes reflect present-day conditions, historical legacies must also be accounted for in effective interventions. This dissertation has sought to advance that understanding by tracing connections between human capital formation, institutional quality, and health outcomes across temporal and spatial scales. The evidence establishes that historical patterns of elite numeracy shaped trajectories that influence health today, that cognitive competencies determine how individuals respond to disease risk, that institutions condition the effectiveness of resources directed toward health, and that education policy shapes physical development in ways that reduce inequality. These findings collectively argue for approaches to health improvement that address fundamental determinants rather than focusing exclusively on proximate interventions.

The challenge confronting policymakers and practitioners is not primarily technical; we possess interventions capable of preventing or treating most diseases affecting populations. The challenge is whether populations can access and benefit from these interventions, which depends on deeper conditions of capacity, resources, and institutional development. While medical technologies, health interventions, and policy frameworks can be transferred across borders, the institutional capacity to implement them, the human capital to utilise them effectively, and the sustained resource commitment to maintain coverage cannot be imported or implemented rapidly. Building these foundations takes time, frequently demanding periods that outlast political terms, funding cycles, or institutional mandates. However, the returns to such investments compound over time, establishing conditions under which populations can thrive rather than merely survive. The persistence of health inequalities despite technical solutions reflects this fundamental challenge: interventions often target immediate health outcomes while structural determinants rooted in institutional capacity, human capital deficits, and resource constraints continuously shape population health paths.

The work of improving population health is thus fundamentally the work of building human capital and strengthening institutions, recognising these as investments whose benefits extend far beyond any single policy domain. Education shapes not only economic productivity but also health behaviours, physical development, and the capacity to adapt to changing disease environments. Institutions determine not only economic growth but also the effectiveness of health systems, the responsiveness of governance to population needs, and the equity with which resources are distributed. Attending to these structural determinants represents a more ambitious and longer-term approach than focusing on disease-specific interventions, yet it may also prove more transformative in establishing the conditions for health equity across populations and generations.

The four chapters of this dissertation have examined different dimensions of how human capital and institutions shape health. However, they converge on a common conclusion: differences in population health reflect disparities in human capital levels and institutional quality, as well as the pathways through which these shape health outcomes. Addressing these disparities requires confronting not merely the symptoms of ill health but the foundational inequalities in human capital and institutional capacity that produce those symptoms. This is challenging work, demanding sustained, coordinated effort across typically traditionally separate policy domains. Nevertheless, it is essential if the aim is not only to treat disease but to create conditions in which all populations can achieve their full potential for health and well-being.