GlobDev 2022

Proceedings Annual Workshop of the AIS Special Interest Group for ICT in Global Development

12-10-2022

A Global Health Analysis of Socio-Economic Determinants of Health, and Human Digital Development, Health Equity and mHealth

Sajda Qureshi

Martina Clarke

Lisa Kiemde

A Global Health Analysis of Socio-Economic Determinants of Health, and Human Digital Development, Health Equity and mHealth

Sajda Qureshi, Martina Clarke, Lisa Kiemde
College of Information Systems &Technology University of Nebraska Omaha
squreshi@mail.unomaha.edu, martinaclarke@unomaha.edu, lgmorton@unomaha.edu

Paper Category: Research Paper

ABSTRACT

Access to the internet, often via mobile devices, provides individuals with the ability to access the resources and economic opportunities required to live the lives they choose. Using data drawn from the World Health Organization, United Nations Development Program, and World Bank, two levels of analysis are conducted to answer the research questions: "What is the relationship between social determinants of health and human digital development?" and, "What is the relationship between health equity and mHealth?". First, multiple regression was utilized to test two hypotheses, and second, a k-means cluster analysis was carried out categorize the countries based on these variables. Our results suggest that there is correlation between social determinants of health and human digital development; except in the case of the homelessness variable. Of the health equity variables, only the GINI index correlates with the mobile health index. A four-cluster solution in the cluster analysis illustrates that the majority of countries demonstrate low mHealth, Human Digital Development, GINI and high Education Inequality and Life Expectancy inequality. These findings have implications for how human digital development and mobile health can address social determinants of health. Future research will need to delve deeper into these connections.

Keywords: Socio-economic determinants of Health, mHealth, Health Equity, Human Digital Development

INTRODUCTION

This study focuses on the socio-economic determinants of health of those at the margins in an increasingly interconnected data intensive society. Individuals considered to be on the margins are those who lack the ability and freedom to live the lives they desire. As vulnerable populations fall into poverty due to war as refugees, homelessness, lack of education and ability to earn a living, they enter the margins of society. The constraints facing these individuals do not fully transcend possibilities of digital transformation. Digital transformation of a society takes place when technologies play a significant role in the creation, as well as the reinforcement of changes taking place in the lives of people. In the development context, digital transformation is changing the way improvements are taking place in the lives of people, their communities, and nations. Graham and Anwar (2019) propose the emergence of a 'planetary labor market' in digital work, which is the use of online outsourcing platforms that host jobs ranging from machine learning system training to transcription to live personal assistance and everything in between. These platforms allow for global work whereby large numbers of people are able to find employers beyond single locations on a planetary scale. This planetary labor market is increasing inequities between workers and employers because it brings about both asymmetrical scalar relationships and uneven spatial ones.

Research has shown that there is a correlation between the use of ICTs and economic performance in some geographic regions (Samoilenko 2008, Levendis & Lee 2013, Qureshi 2014, Mayer et al 2020, Chatterjee 2020, Adeleye et. al. 2021). Recent studies suggest that the effect of ICT adoption differs significantly across sub-regions and ICT innovation enhances the impact of trade on growth (Adeleye et. al. 2021). This suggests that geographic and technological distances play a vital role in the extent to which ICTs enable economic growth in some regions (Wang & Zhao 2018). By using the innovations in ICTs, people are able to improve their lives through the development of their capabilities to use digital advances. In their analysis of spatial patterns of ICT access and use, Pick et. al. (2021) found that the most important and prevalent determinant of usage of technologies is the human development index, defined by the UN as an equal weighting of life expectancy, years of schooling, and gross national income (GNI) per capita. These socio-economic factors create inequities in health outcomes whereby people living in locations with greater resources will have better health outcomes than those who live in rural or areas with limited resources. There appears to be a link between mobile internet access and people's ability to access the resources they require to stay healthy (Qureshi & Xiong, 2021). Individuals at the margins become vulnerable to digital biopolitics or efforts by governments and corporations to maximize knowledge and control of populations using digital means for political and economic power.

In this datafied society, digital transformation offers cause for activism and fight for human rights and freedoms (Qureshi, 2021). In adding to this body of knowledge, this paper investigates:

1. The relationship between mobile health (mHealth) and health equity measured in terms of life expectancy at birth, adolescent birth rate, maternal mortality rate, the Gini index and inequality in life expectancy.
2. The relationship between social determinants of health and the digital transformation of global health measured through and index created for this purpose: human digital development.

This paper answers the following research questions:

1. What is the relationship between social determinants of health and human digital development?
2. What is the relationship between health equity and mHealth?

Data drawn from the World Health Organization, United Nations Development Program and World Bank is used to identify and analyze location specific and location independent factors affecting inequities. The contribution of this study is in measuring the relationships between social determinants of health and human digital development and in understanding the relationship between mHealth and health equity. Countries are classified into categories based on their geographical and economic performance in relation to the mHealth index and the human digital development index. It offers insights on the distribution of economic activity of those at the margins in an increasingly interconnected datafied society.

THEORETICAL BACKGROUND

Digital Transformation

Digital transformation is taking place globally as development efforts evolve with the growth of mobile and internet usage in the world's economic margins. Vial (2019) offers a comprehensive review of digital transformation whereby technologies play a vital role in the creation, as well as the reinforcement of disruptions taking place at the society and industry levels. In the development context, digital transformation is changing the way improvements are taking place in the lives of people, their communities, and nations. Graham (2019) suggests that as more people and places join this global digital network, digital production can transform the lives of those on the world's economic margins. In addition, he reports that places which were once economically marginal may be able to transcend the constraints of space, organizational structure, social structure, and politics. In recognizing that the digital information of services, and goods are embedded in broader socio-technical systems, the digitalization of goods, productions, and services is crucial to an increasing amount of economic value creation. On the other hand, digital production of commodities or services that are themselves digital or digitally transmissible also add to the economic value. Such transformation of global processes and the production of goods and services comprise the digital transformation of the global economy. Development efforts so far have focused on the implementation of ICTs as agents of change. Some argue, that ICT4D projects have increased inequality in the pursuit of development and failed the poor (Unwin 2017, Harris 2016). It is also unclear whether in the economics of innovation, firms located in clusters benefit from territorial learning and knowledge spillovers (Huber 2012).

Economic geography, or the study of the geography of economic activities, evolved from a focus on commercial activities and resource exploitation for economic gain. While the focus of the field includes sectors of economic activity, including understanding the capitalist world economy, firms, economic development, restructuring, and labor, economic geography has grown to encompass social, cultural, political, and institutional influences that affect the geography of economic activities. The infrastructure that makes up the "network of networks" and the spatial patterns that have emerged in the Internet's brief existence, which have revealed a global bias towards the world's cities, provide a focal point for this research (Malecki, 2002). Mudambi, Narula and Santangelo (2018):

> "*The distribution of creative economic activity over space has been viewed from three distinct perspectives: International business focuses on the multinational enterprise and the location of activities across national borders; economic geography studies the characteristics of the location site; and innovation scholars are mainly concerned with the technologies and knowledge that arises from the interaction of the location and the creativity of actors*." (Mudambi et al 2018, p.1)

Digital transformation is taking place globally as development efforts evolve with the growth of mHealth data. In order to investigate the role of mHealth data as a driver of innovation, its transformation of the digital ecosystem needs to be understood. Jarvenpaa and Markus (2016) offered a data perspective that integrates genetic, health, genealogical, and lifestyle data into digital platforms that involve unprecedented data management challenges because of their scale and multidimensionality. A key role for artificial intelligence in global health can be found in the volume and multidimensionality of health data generated by telehealth and mobile devices all over the world (Krittanawong & Kaplin, 2021, Wahl et al 2018; Schwalbe & Wahl, 2020; Hadley et al 2020).

Human development is defined as people's ability to live the lives they want. It is most often measured by the Human Development Index (HDI), which is a summary measure of average achievement in key dimensions of human development: a long and healthy life, being knowledgeable and have a decent standard of living. The HDI is the geometric mean of normalized indices for each of the three dimensions where the health dimension is assessed by life expectancy at birth, the education dimension is measured by mean of years of schooling for adults aged 25 years and more and expected years of schooling for children of school entering age. The standard of living dimension is measured by gross national income per capita. The HDI uses the logarithm of income to reflect the diminishing importance of income with increasing Gross National Income. The scores for the three HDI dimension indices are then aggregated into a composite index using geometric mean (UNDP 2022).

Human Digital Development Index: In relation to human development, digital transformation can give people at the margins the freedom to live the lives they want. A Human Digital Development index is created for the purpose of this research. This index comprises the HDI and percentage of a country’s population that use the internet and mobile phones.

Social Determinants of Health (SDOH)

According to the World Health Organization (WHO), health is largely determined by a person’s “circumstance and environment” (World Health Organization, n.d.). This refers to the factors which are called social determinants of health (SDOH). These are not only the socio-economic factors such as education, income, and occupation (Adler, 2002; CDC, 2018; APA, 2020; Clarke et al. 2021). They also include factors such as race, religious affiliations, gender, geographic location, age, disability, and sexual orientation (Georgsson & Mattias, 2016; Marmot, 2007; Adler & Ostrove, 1999; Qureshi, 2021). It is a well-known fact that if you have more money, you will most likely be healthier. However, it is not only wealth that determines health (Adelman, 2008; Marmot, 2007; Castañeda et al., 2015).

According to Marmot (2007), employment type can change someone's risk of heart disease. This was evident during the pandemic. Populations with more access to social opportunities had access to the best treatments (Georgsson & Mattias, 2016; Marmot, 2007; Adler & Ostrove, 1999; Qureshi, 2021). Adler and Newman discovered the major determinants of health: health care, environmental exposures, and lifestyle and healthy behaviors (Adler & Newman, 2002). Low-income populations, food insecure populations, housing insecure populations, children, minority populations, and substance dependent populations are all SDOH populations which are explicitly mentioned by Adler & Newman (2002). Other SDOH communities that will be considered are survivors of domestic violence, immigrants, refugees, LGBTQ+, non-native English speakers, and those who have a disability or are impaired. These are also SDOH due to the lack of access to healthcare (APA, 2020; Castañeda et al., 2015). In this paper the SDOH are described as follows:

Homelessness and Instability: Refugees, asylum seekers, and internally displaced people reflect the growing number of people living on the periphery of society. Unprotected by international agreements on asylum seekers and refugees, most internally displaced persons (IDPs), nonetheless, suffer from severe deprivations that can sometimes last for decades (UNDP 2022).

Education: Expected years of schooling is the number of years a child of school entrance age is expected to spend at school, or university, including years spent on repetition. It is the sum of the age-specific enrolment ratios for primary, secondary, post-secondary non-tertiary and tertiary education (World Bank 2022). *Mean years of schooling (MYS)* is the average number of completed years of education of a population and is a widely used measure of a country's stock of human capital (UNDP 2022).

Environment: CO_2 emissions (metric tons per capita) reflect the quality of air available. Human-caused greenhouse gas (GHG) emissions drive climate change. About 60% of GHG emissions come from just 10 countries, while the 100 least-emitting contributed less than 3%. Energy makes up nearly three-quarters of global emissions, followed by agriculture. Within the energy sector, the largest emitting sector is electricity and heat generation, followed by transportation and manufacturing. Land use, land use-change and forestry (LULUCF) are both a source and sink of emissions and key sector to get to net-zero emissions (World Bank 2022).

Rural population with access to electricity: This indicates a level of deprivation. This data is from the “Energy Progress Report” led jointly by the custodian agencies: the International Energy Agency (IEA), the International Renewable Energy Agency (IRENA), the United Nations Statistics Division (UNSD), the World Bank and the World Health Organization (WHO) (see World Bank 2022).

Inequality in education: The unequal distribution of academic resources, including but not limited to school funding, qualified and experienced teachers, books, and technologies to socially excluded communities. These communities tend to be historically disadvantaged and oppressed (UNDP, 2022).

When information technology is thoughtfully implemented, it can bridge gaps created by disparities in health (Deitenbeck et al., 2018; Negash et al., 2018). When SDOH are considered, information technology proves to be sustainable (Deitenbeck et al., 2018; Negash et al., 2018).

Given the above, **Hypothesis 1: High Human Digital Development Index correlates with higher values for social determinants of health.** This means that when people are listed high on the HDI, they will have better opportunities measured in terms of values for social determinants of health such as income, housing, life expectancy, education, and access to electricity. They may also be able to use digital technologies to improve human development outcomes. The better the human digital development outcomes, the greater the stability and lower homelessness, the environment has lower carbon dioxide emissions, higher education levels, lower educational inequality, and a larger rural population with access to electricity.

mHealth

mHealth is the use of mobile devices to promote healthier behaviors and self-education (Kahn et al., 2010; Kiemde & Qureshi, 2021; Kiemde et al., 2021). mHealth is a valuable tool. This can be seen by the more than 40,000 health-related apps available in 2012 to help people manage their health (Boulos et al., 2014). Eighty-five percent of the worldwide population have mobile coverage (ITU, 2020; Qureshi, Xiong, & Deitenbeck et al., 2019; Clarke et al., 2021). This shows the potential for ICT and mHealth to have an impact in a community or an individual's health outcomes.

mHealth can assist patients in receiving information and, as a result, speed up the diagnosing process (Clarke et al., 2016; Clarke et al., 2020; Clarke et al., 2021). These technologies can help reduce a patient's out-of-pocket expenses. They aid in the reinforcement of healthy habits including sleeping, eating, and exercising. It can serve as a monitoring mechanism for people with chronic health problems. They can assist in informing people about probable diagnosis, as well as how to treat ailments. It can act as both a direct communication channel and a helpline between healthcare providers and their patients. It was most recently used to track the pandemic's outbreak (Deitenbeck et al., 2018; Negash et al., 2018).

Qureshi and Xiong (2019) developed a mHealth index to better understand how mobile devices are used to provide equitable healthcare. They discovered a link between mHealth, social inequalities in life expectancy, and educational attainment on Human Development in all countries throughout the world. Their research showed a link between mHealth, social inequalities in healthcare delivery, and human development outcomes. They observed a considerable positive link between the SDOH and health equity in relation to mHealth use at the global level in a second study (Qureshi & Xiong, 2019).

Since it has already demonstrated compelling potential for addressing SDOH, mHealth is being used more frequently by both health care providers and patients. mHealth apps are assisting individuals in becoming healthier, and they can bridge the gap between rural and isolated populations (Boulos et al., 2014). These apps addressed issues such as chronic disease management, access to relevant health information, exercise and food intake tracking, follow-up care, and basic diagnostics for minor medical issues (Silvia, Rodrigues, Diez, Lopez-Coronado, Saleem, 2015). A *mobile health index* is created for this research, which comprises life expectancy and Internet mobile phone usage.

Health Equity

The concept of heath equity arose from the belief that differences in social and economic backgrounds of people lead to differences in their ability to access health care. In other words, groups of people who are already socially disadvantaged due to their poverty, gender, racial, ethnic, or religious backgrounds are further disadvantaged with respect to their health. Braveman and Gruskin (2003) offered a conceptual definition that they operationalize by stating that "*equity in health is the absence of systematic disparities in health (or in the major SDOH) between groups with different levels of underlying social advantage/disadvantage—that is, wealth, power, or prestige…. health is essential to wellbeing and to overcoming other effects of social disadvantage*." (Braveman and Gruskin 2003, p.254). According to the CDC, health equity is achieved when everyone can reach their full health potential and no one is hampered by their SDOH. According to Clarke et al. (2016), there are impediments to receiving this information. They discovered that one's capacity to find relevant and reputable information was influenced by "age, education, and household income" (Clarke et al., 2016). If people have the access to seek healthcare, then they will be healthier (James, 2013).

Equitable health refers to the ability to be healthy in the absence of preexisting conditions. (Qureshi & Xiong, 2021; Qureshi & Xiong, 2019; Clarke et al., 2021; Marmot, 2007). It is an opportunity for people to achieve the highest level of physical and mental well-being that their biological limitations will allow (Qureshi & Xiong, 2021; Qureshi & Xiong, 2019; Clarke et al., 2021; Marmot, 2007). A person who could improve their health but chooses not to, does not face health disparity. On the other hand, a person who is unable to build healthy habits or seek medical care due to a lack of social chances has not been given the opportunity to reach their full potential in terms of physical and mental health (Marmot, 2007; Braveman, 2003).

In this sense, the impact of one's social opportunities will reflect and impact the community's health. This in turn will also impact the economy, which can influence both the individual and community's health (Khan et al., 2010). The process to find credible information is stressful. An individual that is already stressed due to their social disparities will likely have a challenging time finding information and resources (Kiemde & Qureshi, 2021). Outcomes of health inequities can be measured in terms of:

Life expectancy at birth: The number of years a person can expect to live. Life expectancy is based on an estimate of the average age that members of a particular population group will be when they die (World Bank 2022).

The Gini Index: A summary measure of income inequality. The Gini coefficient incorporates the detailed shares data into a single statistic, which summarizes the dispersion of income across the entire income distribution (World Bank, 2022).

Inequality in life expectancy: Inequality in the distribution of expected span of life-based on data from survival tables estimated using the Atkinson inequality index (UNDP, 2022).

Adolescent birth rate: Births per 1000 women aged 15-19 years, technically known as the age-specific fertility rate provides a basic measure of reproductive health focusing on a vulnerable group of adolescent women. There is widespread agreement in the literature that women who become pregnant and give birth early in their reproductive lives face increased risks of complications or even death during pregnancy and birth, and their children are also at risk (WHO, 2022).

Maternal Mortality Rate: These are deaths per 100 000 live births. A woman's lifetime risk of maternal death is the probability that a 15-year-old woman will eventually die from a maternal cause (WHO, 2022).

Given the above, we present the **Hypothesis 2: High mHealth will correlate with high levels of health equity.** Where high levels of health equity are measured by high life expectancy at birth, GINI index, and low inequality in life expectancy, adolescent birth rate and maternal mortality rate.

METHODOLOGY

A quantitative deductive approach was employed to investigate the following two research questions:

1. What is the relationship between social determinants of health and human digital development?
2. What is the relationship between health equity and mHealth?

Data was collected from a combination of sources, including The World Health Organization, World Bank, and the United Nations Statistics Division. Data was collected for 188 countries as they had complete data points for the variables selected. For each variable, data from 2015 to 2021 was collected and cleaned (United Nations 2022, World Bank 2022, World Health Organization 2022).

For the purpose of this study, the following indices were created to be able to test the models and hypotheses. The data are defined as follows**:**

Mobile health index: created for this research comprises of life expectancy and Internet mobile phone usage.

Human Digital Development Index (HDDI): created for this research consists of the HDI and percentage of a country's population that use the Internet and mobile phones.

Table 1: Categories of HDDI

Categories	Range	Mean Digital HDI
low digital HDI	0.113 – 0.520	0.362
medium digital HDI	0.523 – 0.743	0.641
high digital HDI	0.754 – 0.948	0.865
very high digital HDI	0.952 – 1.754	1.109

Data Analysis

Two levels of analysis were conducted to answer the research questions. First multiple regression was utilized to test two hypotheses**:**

> Hypothesis 1: High Human Digital Development Index correlates with higher values for social determinants of health; and
>
> Hypothesis 2: High mHealth will correlate with high levels of health equity.

First, regression was employed to test Hypothesis 1 and 2. The variables used to test the hypotheses are described below:

Table 2: Summary of Variables used to test Hypotheses 1 and 2

SDOH Variables	Health Equity Variables
Homelessness and instability	Life expectancy at birth
Education	Adolescent birth rate
Environment	Maternal mortality rate

Rural population with access to electricity	The Gini index
Inequality in education	Inequality in life expectancy

After the regression provided insights into the correlations between our key variables, we performed a k means cluster analysis to categorize the countries based on these variables (Huber, 2012). The results and analysis are described in the following sections. Analysis of Variance (ANOVA) was used to determine if there is a statistically significant difference between the health equity variables.

RESULTS AND ANALYSIS

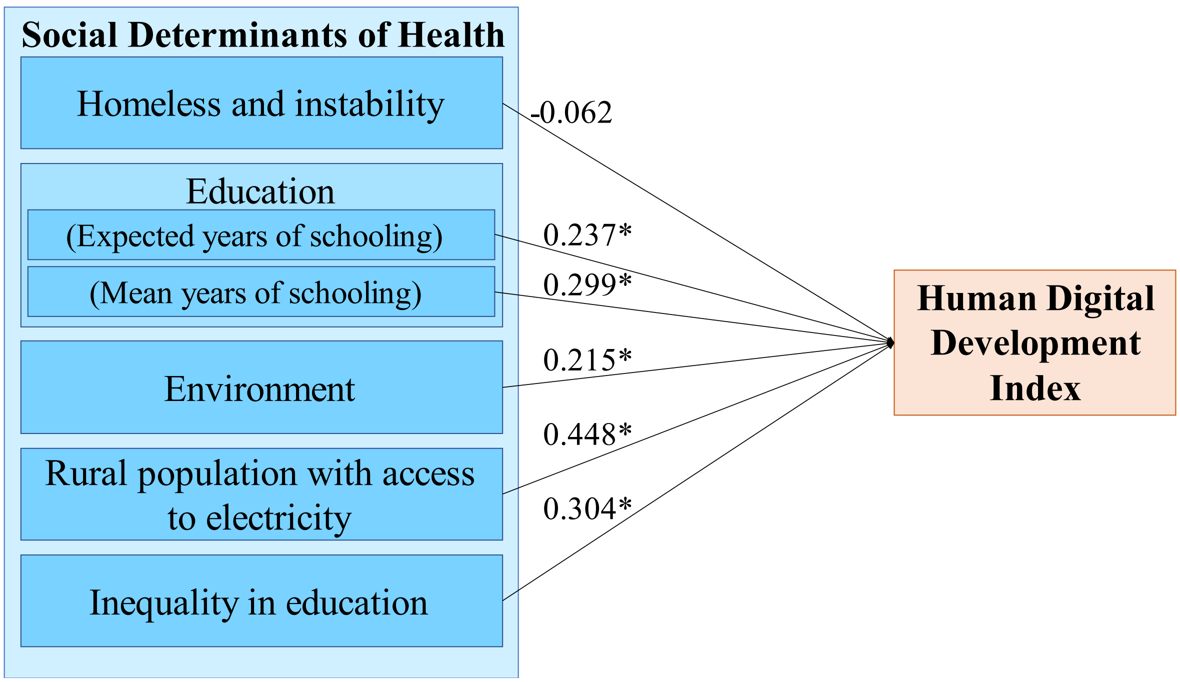
In this section, the relationship between mHealth data and the digital transformation is investigated. Linear regression was performed to test the initial hypotheses. Data drawn from the World Health Organization, United Nations Development Program and World Bank was used to identify and analyze location specific and location independent factors affecting inequities.

Relationship between SDOH and human digital development

The mean value of the human digital development index for all countries was 0.813 with a standard deviation of 0.296. Human digital development index scores ranged from 0.113 – 1.754. The first hypothesis was high human digital development index correlate with higher SDOH. Model 1 illustrates the analysis of SDOH and human digital development. An R^2 of 0.619 suggests that 61.9% of the variance in the human digital development index can be predicted by *Education* (*Expected years of schooling*: $p = 0.004$; *Mean years of schooling*: $p = 0.028$), Environment ($p < 0.001$), *Rural populations with access to electricity* ($p < 0.001$), and *Inequality in Education* ($p < 0.010$). An ANOVA of <0.001 indicates that *Education***,** *Environment***,** *Rural populations with access to electricity***,** and *Inequality in Education* can be used to reliably predict a country's human digital development index. *Homelessness and instability* cannot be used to reliably predict a country's human digital development index. Countries with a higher *Human digital development index* have higher expected years of schooling, mean years of schooling, lower CO_2 emissions, higher percentage of their rural population have access to electricity, and more equal distribution of academic resources.

For countries with a low HDI (<0.55), mean *Human digital development index* was 0.497 (min = 0.113; max = 1.225). Mean *Human digital development index* for countries with a medium HDI (0.55 – 0.70) was 0.616 (min = 0.266; max = 0.952). Mean *Human digital development index* for countries with a high HDI (0.7 – 0.79) was 0.839 (min = 0.350; max = 1.352). For countries with a very high HDI (0.8 – 1.0), mean *Human digital development index* was 1.060 (min = 0.113; max = 1.225). Countries with a higher *Human digital development index* have a higher HDI, higher use of the Internet and mobile phones.

Model 1. SDOH and Human Digital Development



* indicates significance < 0.05. R Squared = 0.619. ANOVA <0.001.

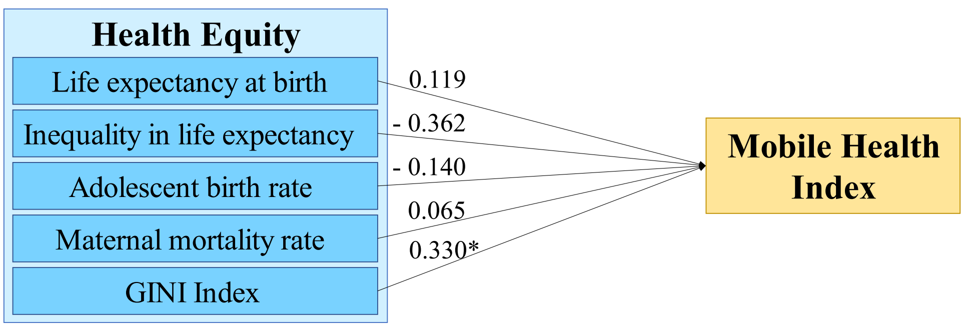
Relationship between health equity and the mobile health index

The mean value of the mobile health index for all countries was 1.525 with a standard deviation of 0.350. Mobile health index scores ranged from 0.763 – 2.594. The second hypothesis was high mHealth will correlate with high levels of health equity. Model 2 illustrates the relationship between health equity and mHealth. An R^2 of 0.660 suggests that 66% of the variance in the mobile health index can be predicted by the *Gini Index* ($p < 0.001$) and *Inequality in life expectancy* ($p = 0.052$). An ANOVA of <0.001 indicates that the *Gini Index* can be used to reliably predict a country's mobile health index. *Life expectancy at birth* ($p = 0.507$), *Adolescent birth rate* (p <

0.093), and *Maternal mortality rate* ($p < 0.483$) cannot reliably predict a country's mobile health index. Countries with a higher *Mobile health index* have higher GNI index and lower equal life expectancy.

For countries with a low HDI (<0.55), mean *Mobile health index* was 1.107 (min = 0.763; max = 1.815). Mean *Mobile health index* for countries with a medium HDI (0.55 – 0.70) was 1.287 (min = 0.895; max = 1.682). Mean *Mobile health index* for countries with a high HDI (0.7 – 0.79) was 1.560 (min = 1.100; max = 2.128). For countries with a very high HDI (0.8 – 1.0), mean *Mobile health index* was 1.842 (min = 0.982; max = 2.594). Countries with a higher *Mobile health index* have higher Internet mobile phone usage and higher life expectancy.

Model 2. Health Equity and Mobile Health Index



* indicates significance < 0.05. R Squared = 0.650. ANOVA found significance.

Cluster Analysis

A k_means cluster analysis was implemented to classify the countries in this sample based on the key indices: *mHealth, Human Digital Development, The Gini Index, Educational Inequality* and *Life expectancy Inequality* (Table 1). Based on this analysis, 175 countries clustered into a four-cluster solution that was most significant.

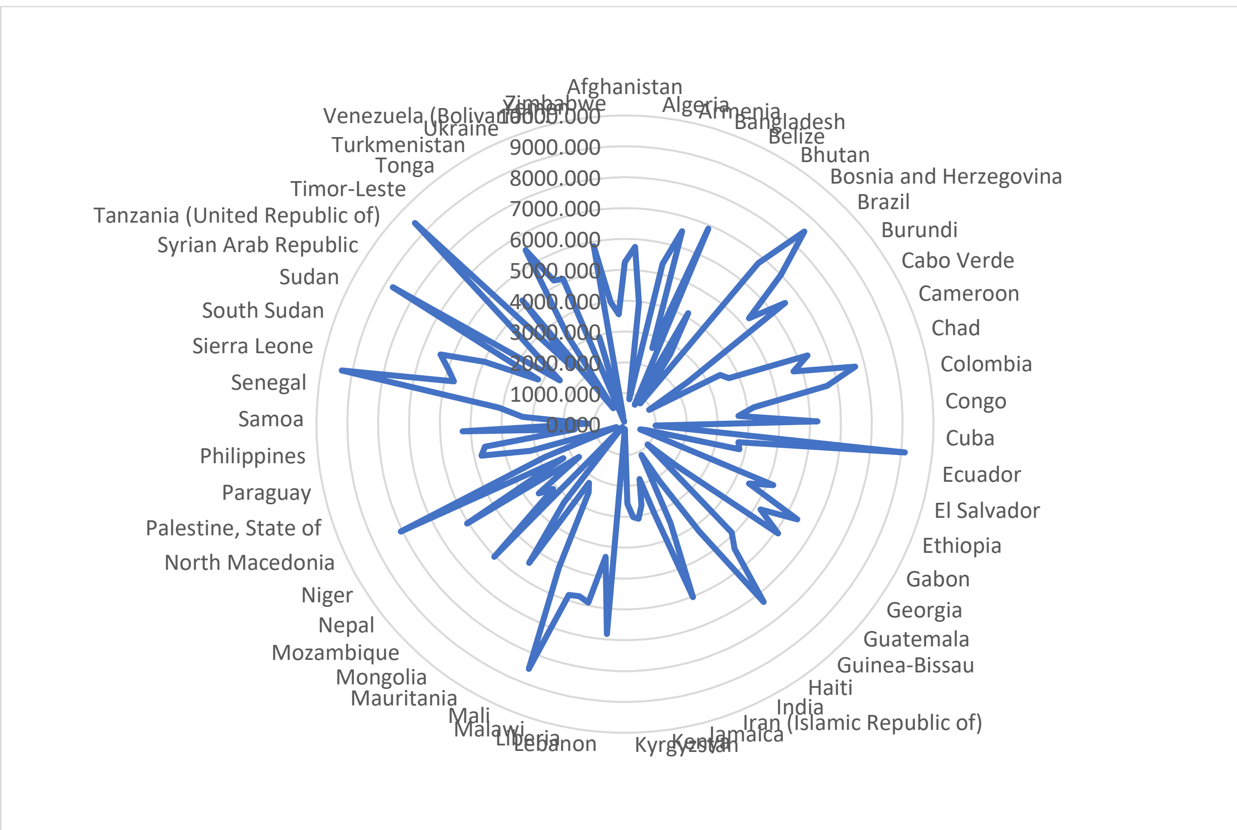
Table 1 k_means cluster analysis to classify 175 countries based on the key indices: *Mobile health, Human Digital Development, The Gini Index, Educational Inequality* and Inequality and *Life expectancy*.

ANOVA	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
mHealth	3.176	3	.063	169	50.137	.000
DigitalHDI	1.892	3	.051	169	37.094	.000
GINI Index	19997888312.908	3	33321218.466	169	600.155	.000
Education Inequality	4116.158	3	142.497	169	28.886	.000
Life Expectancy Inequality	2664.701	3	61.914	169	43.039	.000

Cluster 1: Low mHealth, Human Digital Development, GINI and high Education Inequality and Life Expectancy

Cluster 1 is the largest cluster with 109 countries (Figure 1). This cluster has the lowest *mobile health index* of 1.358, a *Human Digital Development index* of 0.6852, a *GNI Index* of 7278, the highest *Education inequality index* of 24.85, and the highest *Life expectancy inequality index* of 18.93. This cluster has 3% of countries with a very high (0.8 – 1.0) HDI, 37% of countries with a high HDI (0.7 – 0.79), 30% of countries with a medium HDI (0.55 – 0.70), and 30% of countries with a low HDI (<0.55).

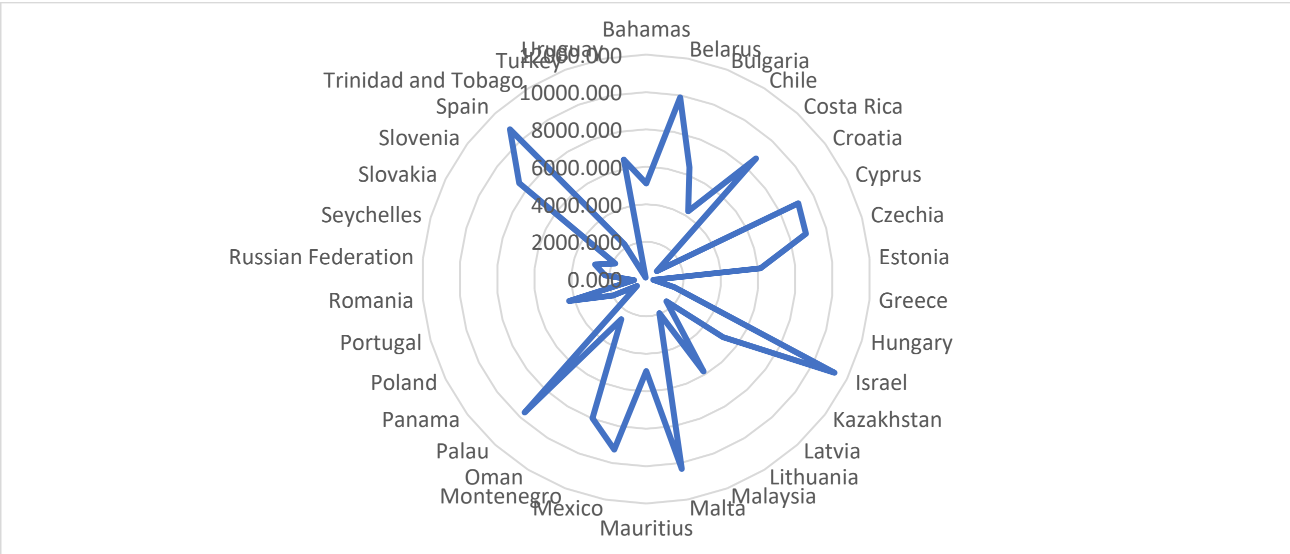
Figure 1 Cluster 1: Low mHealth, Human Digital Development, GINI and high Education Inequality and Life Expectancy



Cluster 2: Rising mHealth, Human Digital Development, GINI and lower Education inequality, Life expectancy inequality

Cluster 2 is the second largest cluster with 35 countries (Figure 2). The countries in this cluster demonstrate a *mHealth index* of 1.772, *Human Digital Development index* of 1.0142, a rising *GNI index* of 27942, and lower *education inequality index* of 7.7186 and *life expectancy inequality index* of 5.942. This cluster includes 94% of countries with a very high (0.8 – 1.0) HDI and 6% of countries with a high HDI (0.7 – 0.79).

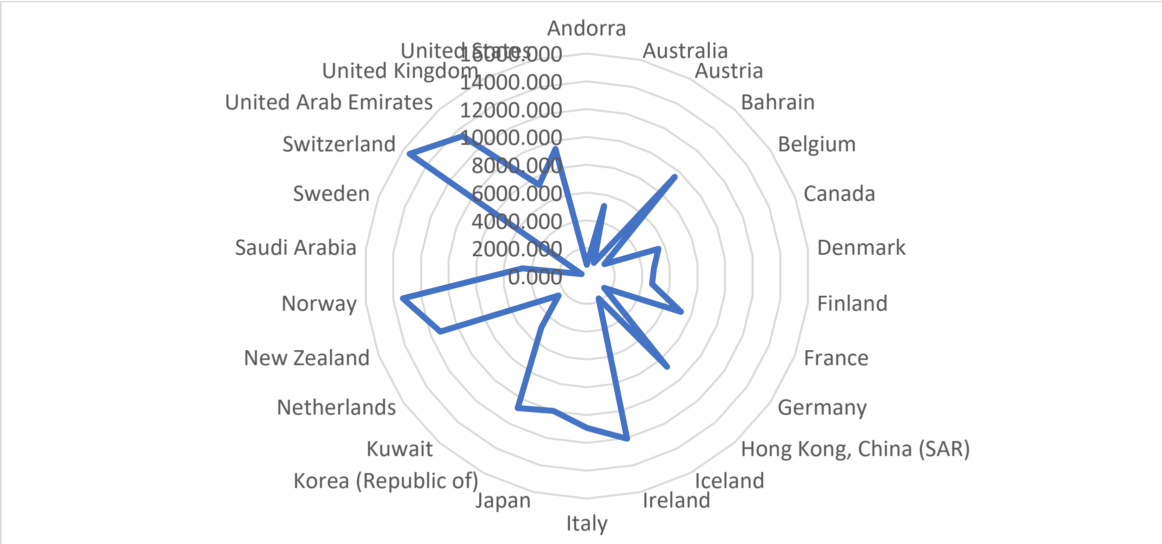
Figure 2 Cluster 2: Rising mHealth, Human Digital Development, GINI and lower Education inequality, Life expectancy inequality



Cluster 3: Higher a mHealth, Human Digital Development index, GNI index and the lowest Education inequality and low Life expectancy inequality.

Cluster 3 is the third cluster with 26 countries (Figure 3). They illustrate a higher *mHealth index* of 1.903, *Human Digital Development index* of 1.096, *GNI index* of 52493 and the lowest *Education inequality* of 6.661, and low *Life expectancy inequality* of 3.717. This cluster is 100% of countries with a very high (0.8 – 1.0) HDI.

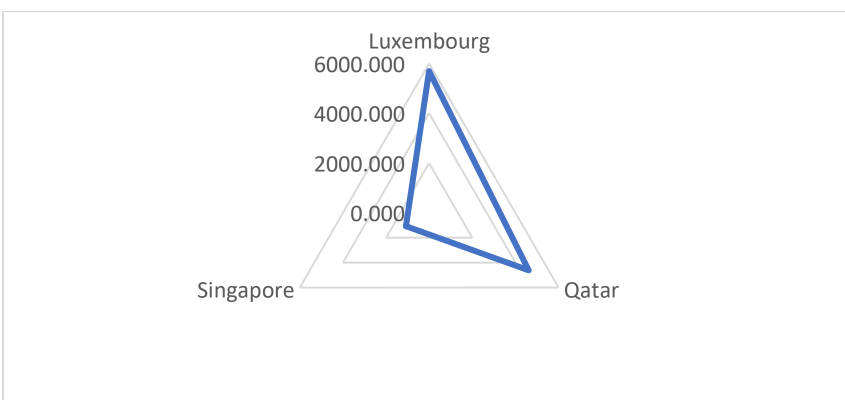
Figure 3 Cluster 3: Higher a mHealth, Human Digital Development index, GNI index and the lowest Education inequality and low Life expectancy inequality.



Cluster 4: Highest mHealth, Human Digital Development, GNI and higher Education Inequality and lowest Life expectancy inequality

Cluster 4 contains 3 countries (Figure **4**). The countries in this cluster have the highest *mHealth index* of 1.992, *Human Digital Development index* of 1.1834, *GNI index* of 85.120 and higher *Education inequality index* of 9.667 and *Lowest life expectancy inequality* of 3.514. This cluster includes 100% of countries with a very high (0.8 – 1.0) HDI.

Figure 4 **Cluster 4: Highest mHealth, Human Digital Development, GNI and higher Education Inequality and lowest Life expectancy inequality**



Countries in the smallest cluster 4 with only 3 countries have the highest *mHealth*, *Human Digital Development*, *GNI* and higher *Education Inequality* and lowest *Life expectancy inequality*. In contrast, the majority of countries in the world fall into the first cluster with 109 countries, which demonstrate low *mHealth*, *Human Digital Development*, *GINI* and high *Education Inequality* and *Life Expectancy inequality*. The following section explains this analysis in the light of the two research questions being investigated.

DISCUSSION

The first hypothesis was high human digital development index correlate with higher SDOH. As seen in the model 1, this is true for *Education*, *Environment*, *Rural populations with access to electricity*, and *Inequality in Education*. However, for *Homelessness and Instability*, the beta value was negative and not significant. Therefore, in the case of refugees compared to the human digital development index. This could indicate that the values for *Homelessness and Instability* are influenced by the large number of refugees whose countries of origin are in flux, leaving them homeless and stateless. The inverse relationship between *homelessness and instability* and the *human digital development* index shows that the greater the homelessness and instability, the lower the human digital development. Furthermore, the data suggests that the mean years of schooling was less significant than the expected years of schooling. Expected years of schooling is a prediction for those who are currently entering school. Whereas mean years of schooling shows the amount of education within the current workforce.

The second hypothesis was high mHealth will correlate with high levels of health equity. The data analyzed shows that there is not enough evidence to reject the null hypothesis of there being no difference between the variables. The only variable found significant was the GINI index, which shows the income inequality. The adjusted R squared value is high. This might be due to the independent variables being tested. In future tests, health equity variable should not just target the health of women and newborns.

The contribution of this study is in measuring the relationships between social determinants of health and human digital development; and in understanding the relationship between *mHealth* and *health equity*. Countries are classified into categories based on their geographical and economic performance in relation to the mHealth index and the human digital development index. It offers insights on the distribution of economic activity of the individuals at the margins in an increasingly interconnected datafied society.

SUMMARY AND CONCLUSIONS

The relationship between social determinants of health and human digital development, as well as the relationship between health equity and mHealth, was investigated in this paper. Two levels of analysis were performed to answer the research questions: "What is the relationship between social determinants of health and human digital development?" and, "What is the relationship between health equity and mHealth?". First, multiple regression was employed to test two hypotheses and second, a k-means cluster analysis was carried out to categorize the countries based on these variables. Our results suggest that there is correlation between social determinants of health and human digital development; except in the case of the homelessness variable. Of the health equity variables, only the GINI index correlates with the mobile health index. A four-cluster solution in the cluster analysis illustrates that the majority of countries demonstrate low mHealth, Human Digital Development, GINI and high Education Inequality and Life Expectancy inequality. In light of these findings, mobile health and human digital development may enable the addressing of social determinants of health. This relationship will need to be explored in greater detail in future research.

References

Adeleye, B.G., Adedoyin, F. & S. Nathaniel (2021) The criticality of ICT-trade nexus on economic and inclusive growth, Information Technology for Development, 27:2, 293-313, DOI: 10.1080/02681102.2020.1840323

Adelman, Larry. "Unnatural Causes: In Sickness and in Wealth." Kanopy, commentary by Nicholas Christakis and Sir Michael Marmot, 2008, kanopy.com/video/sickness-and-wealth

Adler, Nancy & Ostrove, Joan. (1999). Socioeconomic Status and Health: What We Know and What We Don't. Annals of the New York Academy of Sciences. 896. 3-15. 10.1111/j.1749-6632.1999.tb08101.x.

Adler, Nancy E. and Katherine Newman. "Socioeconomic Disparities in Health: Pathways and Policies Inequality in Education, Income, and Occupation Exacerbates he gaps Between the Health 'Haves' and 'Have-nots'" (2002). Health Aff (Millwood). DOI:10.1377/hlthaff.21.2.60

Angwin Jlk MS, Kirchner L,(2016) Machine bias: ProPublica, 2016. https://www.propublica.

APA "Work, Stress, and Health & Socioeconomic Status." (2020). American Psychological Association. https://www.apa.org/pi/ses/resources/publications/work-stress-health

Boulos, M. N., Brewer, A. C., Karimkhani, C., Buller, D. B., & Dellavalle, R. P. (2014). Mobile medical and health apps: state of the art, concerns, regulatory control and certification. *Online journal of public health informatics*, *5*(3), 229. https://doi.org/10.5210/ojphi.v5i3.4814

Braveman, Paula and S Gruskin (2003). Defining equity in health. *J Epidemiol Community Health 57: 254-258.* https://jech.bmj.com/content/57/4/254

Castañeda, H., Holmes, S. M., Madrigal, D. S., Young, M. E. D., Beyeler, N., & Quesada, J. (2015). Immigration as a social determinant of health. Annual review of public health, 36, 375-392.

CDC "Health Disparities in Cancer: Factors That Contribute to Health Disparities in Cancer." (2018). Division of Cancer Prevention and Control, Centers for Disease Control and Prevention. https://www.cdc.gov/cancer/healthdisparities/basic_info/challenges.htm

Centers for Disease Control and Prevention. (2021, September 30). Social Determinants of Health. Centers for Disease Control and Prevention. Retrieved February 26, 2022, from https://www.cdc.gov/socialdeterminants/index.htm

Chatterjee, A. (2020) Financial inclusion, information and communication technology diffusion, and economic growth: a panel data analysis, Information Technology for Development, 26:3, 607-635, DOI: 10.1080/02681102.2020.1734770

Clarke M.A. et al. (2021) An mHealth Approach to Addressing Health Inequity. In: Kalra J., Lightner N.J., Taiar R. (eds) Advances in Human Factors and Ergonomics in Healthcare and Medical Devices. AHFE 2021. Lecture Notes in Networks and Systems, vol 263. Springer, Cham. https://doi.org/10.1007/978-3-030-80744-3_4

Clarke, M. A., Fruhling, A. L., Sitorius, M., Windle, T. A., Bernard, T. L., & Windle, J. R. (2020). Impact of Age on Patients' Communication and Technology Preferences in the Era of Meaningful Use: Mixed Methods Study. Journal of Medical Internet Research, 22(6). https://doi.org/10.2196/13470

Clarke, M. A., Moore, J. L., Steege, L. M., Koopman, R. J., Belden, J. L., Canfield, S. M., Meadows, S. E., Elliott, S. G., & Kim, M. S. (2016). Health information needs, sources, and barriers of primary care patients to achieve patient-centered care: A literature review. Health Informatics Journal, 22(4), 992–1016. https://doi.org/10.1177/1460458215602939

Deitenbeck, Beck; Sajda Qureshi, Jason Xiong. "The Role of mHealth for Equitable Access to Healthcare for Rural Residents." (2018). Association for Information Systems. https://aisel.aisnet.org/amcis2018/Health/Presentations/12/

Georgsson, & Mattias. (2016, January 08). Quantifying usability: An evaluation of a diabetes mHealth system on effectiveness, efficiency, and satisfaction metrics with associated user characteristics. Retrieved from http://www.diva-portal.org/smash/record.jsf?pid=diva2:892108&dswid=4553

Graham, M (2019). Changing Connectivity and Digital Economies at Global Margins, In: Graham, M. (Ed.). (2019). Digital economies at global margins. MIT Press.

Graham, M., & Anwar, M. A. (2019). The global gig economy: Towards a planetary labour market?. First Monday, 24(4). https://doi.org/10.5210/fm.v24i4.9913

Hadley TD, Pettit RW, Malik T, Khoei AA, Salihu HM. (2020) Artificial Intelligence in Global Health -A Framework and Strategy for Adoption and Sustainability. Int J MCH AIDS. 2020;9(1):121-127. doi: 10.21106/ijma.296. Epub 2020 Feb 10. PMID: 32123635; PMCID: PMC7031870.

Harris, R. W. (2016). How ICT4D research fails the poor. Information Technology for Development, 22(1), 177-192.

Huber, F. (2012). Do clusters really matter for innovation practices in information technology? questioning the significance of technological knowledge spillovers. *Journal of Economic Geography, 12*(1), 107.

ITU (International Telecommunication Union). 2020. "ICT Facts and Figures 2020." www.itu.int/en/ITU-D/Statistics/Pages/stat/. Accessed 2 September 2020.

James, J. (2013). Patient Engagement. Health Affairs: Health Policy Brief. https://doi.org/10.1377/hpb20130214.898775

Jarvenpaa, S., & Markus, M. L. (2018). Genetic platforms and their commercialization: three tales of digital entrepreneurship. Proceedings of the 51st Hawaii International Conference on System Sciences | 2018

Kahn, J. G., Yang, J. S., & Kahn, J. S. (2010). 'Mobile' health needs and opportunities in developing countries. *Health Affairs, 29*(2), 252-8. doi:http://dx.doi.org.leo.lib.unomaha.edu/10.1377/hlthaff.2009.0965

Kiemde, L., & S. Qureshi, (2021) Social Determinants of Health Inequities and Human Development: Is there a role for mHealth in overcoming health inequities? Proceedings of the 13th Annual AIS SIG GlobDev Pre-ICIS Workshop, Austin, USA, Sunday December 12, 2021

Kiemde, L., Qureshi, S. & M. Clarke (2021) "What is the role of ICTs in addressing health outcomes and limitations from socio-economic status? Proceedings of the 13th Annual AIS SIG GlobDev Pre-ICIS Workshop, Austin, USA, Sunday December 12, 2021

Krittanawong, C., & Kaplin, S. (2021). Artificial intelligence in global health. European Heart Journal (2021) 42, 2321–2330 doi:10.1093/eurheartj/ehab036

Levendis, J. & S. H. Lee (2013) On the endogeneity of telecommunications and economic growth: evidence from Asia, Information Technology for Development, 19:1, 62-85, DOI: 10.1080/02681102.2012.694793

Malecki. (2002). The Economic Geography of the Internet's Infrastructure. Economic Geography, 78(4), 399–424. https://doi.org/10.1111/j.1944-8287.2002.tb00193.x
Management, 38:1, 2-20, DOI: 10.1080/10580530.2020.1732531

Marmot, Michael (2007). Achieving health equity: from root causes to fair outcomes. *Lancet 370:1153-63.* DOI:10.1016/S0140-6736(07)61385-3

Mayer, W., Madden, G. & W. Chen (2020) Broadband and economic growth: a reassessment, Information Technology for Development, 26:1, 128-145, DOI: 10.1080/02681102.2019.1586631

Movement Advancement Project: State Profiles. Movement Advancement Project | State Profiles. (n.d.). Retrieved February 28, 2022, from https://www.lgbtmap.org/equality-maps/profile_state/NE

Mudambi, R., Narula, R., & Santangelo, G. D. (2018). Location, collocation and innovation by multinational enterprises: A research agenda. Industry and innovation, 25(3), 229-241.
org/article/machine-bias-risk-assessments-in-criminal-sentencing

Pampel, Fred C., Patrick M. Krueger and Justin T. Denney. "Socioeconomic Disparities in Health Behaviors" (2010). Annu. Rev. Sociol. 36. DOI:10.1146/annurev.soc.012809.102529

Pick, J. Sarkar, A. & E. Parrish (2021) The Latin American and Caribbean digital divide: a geospatial and multivariate analysis, Information Technology for Development, 27:2, 235-262, DOI: 10.1080/02681102.2020.1805398

Qureshi, S. (2014) Theory to Inform Practice to Build Theory: Are Emerging Economies in a Cyclical Relationship with their Information and Communication Technologies?, Information Technology for Development, 20:4, 293-295, DOI: 10.1080/02681102.2014.962939

Qureshi, S. (2021) Pandemics within the pandemic: confronting socio-economic inequities in a datafied world, Information Technology for Development, 27:2, 151-170, DOI: 10.1080/02681102.2021.1911020

Qureshi, S., & Xiong, J. (2019). Social determinants of health equity: Does mHealth matter for human development?. Paper presented at 25th Americas Conference on Information Systems, AMCIS 2019, Cancun, Mexico.

Qureshi, S., & Xiong, J. (2021). Equitable healthcare Provision: uncovering the impact of the mobility effect on human development. Information Systems Management, 38(1), 2-20.

Qureshi, Sajda & Xiong, Jason (Jie) (2021) Equitable Healthcare Provision:

Qureshi, Sajda (2021) Pandemics within the pandemic: confronting socioeconomic inequities in a datafied world, Information Technology for Development, 27:2, 151-170, DOI: 10.1080/02681102.2021.1911020

Samoilenko, S. (2008) Contributing factors to information technology investment utilization in transition economies: An empirical investigation, Information Technology for Development, 14:1, 52-75, DOI: 10.1002/itdj.20087=

Schwalbe, N., & Wahl, B. (2020). Artificial intelligence and the future of global health. The Lancet, 395(10236), 1579-1586.

Uncovering the Impact of the Mobility Effect on Human Development, Information Systems

United Nations Development Programme (UNDP) (2018). "Can human development turn the tide on internal displacement?" https://hdr.undp.org/content/can-human-development-turn-tide-internal-displacement Date accessed October 9th 2022

United Nations Development Programme (UNDP) (2022) "Human Development Reports" https://hdr.undp.org/data-center/documentation-and-downloads

Unwin, P. T. H., & Unwin, T. (2017). Reclaiming information and communication technologies for development. Oxford University Press.

Vial, G. "Understanding Digital Transformation: A Review and a Research Agenda." The Journal of Strategic Information Systems : Incorporating International Information Systems 28, no. 2 (2019).

Wahl, B., Cossy-Gantner, A., Germann, S., & Schwalbe, N. R. (2018). Artificial intelligence (AI) and global health: how can AI contribute to health in resource-poor settings?. BMJ global health, 3(4), e000798.

Wang, S. & M. Zhao, A tale of two distances: a study of technological distance, geographic distance and multilocation firms, Journal of Economic Geography, Volume 18, Issue 5, September 2018, Pages 1091–1120, https://doi.org/10.1093/jeg/lby042

World Bank (2022). Data Bank. https://databank.worldbank.org/

World Health Organization (WHO) (2022). "Global Health Observatory" https://www.who.int/data/gho

APPENDIX

For Model 1:

Model Summary for Model 1				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.787[a]	.619	.605	.181185419453032
a. Predictors: (Constant), meanyrsofsch15-21, Refugees/Asylum/IDP/Other 15-20, co2prod15-21, Rural population with access to electricity %, exptdyrsofschl15-21, EduIneq15-21				

ANOVA for Model 1						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.846	6	1.474	44.909	.000[b]
	Residual	5.449	166	.033		
	Total	14.295	172			
a. Dependent Variable: DigitalHDI						
b. Predictors: (Constant), meanyrsofsch15-21, Refugees/Asylum/IDP/Other 15-20, co2prod15-21, Rural population with access to electricity %, exptdyrsofschl15-21, EduIneq15-21						

Coefficients for Model 1						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.198	.150		-1.318	.189
	Refugees/Asylum/IDP/Other 15-20	-5.186E-8	.000	-.062	-1.222	.223
	Rural population with access to electricity %	.004	.001	.448	6.712	.000
	co2prod15-21	.011	.003	.215	3.782	.000
	EduIneq15-21	.006	.002	.304	2.605	.010
	exptdyrsofschl15-21	.023	.008	.237	2.931	.004
	meanyrsofsch15-21	.027	.012	.299	2.211	.028
a. Dependent Variable: DigitalHDI						

For Model 2:

Model Summary for Model 2				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.813[a]	.660	.650	.202108420381431
a. Predictors: (Constant), GNI15-20, Mmr15-21, Abr 2015-2021, LifeExF15-21, LeIneq15-21				

ANOVA for Model 2						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13.73	5	2.746	67.225	.000[b]
	Residual	7.067	173	0.041		
	Total	20.797	178			
a. Dependent Variable: mHealth						
b. Predictors: (Constant), GNI15-20, Mmr15-21, Abr 2015-2021, LifeExF15-21, LeIneq15-21						

Co-efficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.230	.646		1.905	.058
	LeIneq15-21	-.012	.006	-.362	-1.958	.052
	LifeExF15-21	.005	.008	.119	.665	.507
	Abr 2015-2021	-.001	.001	-.140	-1.691	.093
	Mmr15-21	9.567E-5	.000	.065	.703	.483
	GNI15-20	5.864E-6	.000	.330	4.915	.000
a. Dependent Variable: mHealth						