THE EUROPEAN SOCIETY OF MEDICINE
Medical Research Archives, Volume 12 Issue 8

RESEARCH ARTICLE

Human Freedom from Algorithmic Bias: What is the role of Accountability in addressing Health Disparities?

Sajda Qureshi, Ph.D[1]; Blessing Oladokun[2]

[1] D.B. and Paula Varner Professor of Information Systems, Director ITD mHealth Cloud Computing Lab, Department of Information Systems & Quantitative Analysis, College of Information Science & Technology. University of Nebraska at Omaha, 6001 Dodge Street, Omaha, NE 68182-0116
[2] Data Analytics Graduate Assistant, ITD mHealth Cloud Computing Lab, Department of Information Systems & Quantitative Analysis, College of Information Science & Technology. University of Nebraska at Omaha, 6001 Dodge Street, Omaha, NE 68182-0116

OPEN ACCESS

PUBLISHED
31 August 2024

CITATION
Qureshi, S. and Oladokun, B., et al., 2024. Human Freedom from Algorithmic Bias: What is the role of Accountability in addressing Health Disparities? Medical Research Archives, [online] 12(8).
https://doi.org/10.18103/mra.v12i8.5635

DOI
https://doi.org/10.18103/mra.v12i8.5635

ISSN
2375-1924

ABSTRACT

While there are many causes of health disparities, the application of Artificial Intelligence tools in healthcare may have mixed results. The purpose of this paper is to investigate the role of human freedoms and accountability to achieving digital inclusion. It discovers the role of algorithmic bias in mediating the relationship between human freedom and mobile health. The following research questions are investigated: 1) How do human freedoms effect digital inclusion and mobile health? 2) Do human freedoms effect mobile health? And 3) Does AI accountability mediate the relationship between human freedoms and mobile health? The findings suggest that human freedoms are central to digital inclusion and mobile health. Accountability does affect the extent to which digital inclusion can be achieved through human freedoms. AI accountability significantly mediates the relationship between human freedoms and the mobile index. This offers an important contribution in uncovering the role of algorithmic bias in human freedom and mobile health, and of accountability between human freedom and digital inclusion.

Keywords: Mobile Health (mHealth), Algorithmic Bias, Human Freedom, Algorithmic Accountability, Artificial Intelligence (AI), Social Determinants of Health (SDOH), Digital Inclusion

Introduction

Human freedoms are seen to be human rights to certain specific freedoms[1]. Those who have been globally marginalized, such as refugees, are limited in their freedoms due to the ways in which their data is harvested, packaged and used by corporations. Zuboff explains that this surveillance capitalism is the original sin that threatens to take away human freedoms beyond algorithms or sensors, machine intelligence or platforms, to bend those whose data is harvested to the will of the corporations or governments[2]. “Surveillance capitalism is an economic creation, and it is therefore subject to democratic contest, debate, revision, constraint, oversight, and may even be outlawed”[2(p.11)]. On the other hand, digital inclusion encompasses efforts to guarantee that everyone has equal opportunities to access and utilize information and communication technologies. Digital inclusion is needed for mobile health applications to be able to address the needs of people in low resource communities to stay healthy. This concept involves providing affordable Internet service, making Internet-enabled devices available, offering digital literacy training, ensuring quality technical support, creating mobile applications, online content aimed at fostering independence, community engagement, and collaboration. [3]These elements lay the groundwork for integrating mobile technology into healthcare delivery.

Digital technologies like Mobile health (mHealth) technologies, while promising in addressing health disparities, have complex interactions with the SDOH (Social Determinants of Health) that need careful consideration. mHealth technologies offer a means of attaining digital inclusion through access to SDOH resources. Studies by Rogers et al. and Ye & Ma[4,5] illustrate this interaction vividly. Rogers et al.[4] focus on integrating mHealth with SDOH in maternal health, using human factors/ergonomics (HF/E) frame- works to explore solutions like improved transportation access to healthcare services. This approach underscores the potential of mHealth in practical applications, particularly in community-based settings. Similarly, Ye and Ma's study[5] sheds light on how wearable devices and smartphone apps impact physical activity, highlighting the influence of SDOH such as age, gender, and income on technology adoption. Both studies point towards the need for mHealth solutions to be tailored to specific community needs and social contexts, suggesting that technology alone is not a panacea but part of a broader, more holistic approach to health.

Digital inclusion in mHealth applications have potential to address the health inequalities that arise in the adoption of the digital health tools. Substantial strides have been made in the adoption and application of mHealth, accompanied by research that addresses its integration into healthcare systems on a large scale. This progress has underscored the potential of mobile phone technology in improving healthcare system efficiency. mHealth applications have been instrumental in gathering precise data for tracking disease outbreaks, preventing medication shortages, supporting patient adherence to treatment plans, especially among the elderly and hard-to-reach groups, and enhancing overall access to healthcare services, among other advantages. Together, the above studies underscore the complexity of achieving digital inclusion and integrating mHealth with an understanding of the Social Determinants of Health (SDOH) that effect the ability of people to stay healthy. They reveal how digital technologies can both mitigate and exacerbate health disparities, emphasizing the need for culturally sensitive, community-based approaches that consider the multifaceted impacts of SDOH on health outcomes.

As the role of artificial intelligence is exacerbated with the digital technologies that are used, algorithmic accountability becomes a central issue. Digital inclusion and mobile health can be supported through artificial intelligence approaches especially in global health[6]. To address the issue, this paper investigates the connection between human freedoms, accountability and the notion that digital inclusion can be achieved if somehow people are free to overcome the shackles of algorithmic bias. It investigates the relationship between human freedoms, AI accountability and the ability of people to access the resources they need to stay healthy through their mobile phones. In particular, this paper focusses on human freedoms as a means to accessing healthcare resources including socio-economic resources measured in terms of social determinants of health, that help people stay healthy. Central to this investigation are the following research questions: 1) How do human freedoms effect digital inclusion and mobile health? 2) Do human freedoms effect mobile health? And 3) Does AI accountability mediate the relationship between human freedoms and mobile health? Following the development of a theoretical background, this paper offers a conceptual model that is tested through a series of regression analyses. The findings suggest that human freedoms are central to digital inclusion and mobile health. However, accountability does affect the extent to which digital inclusion can be achieved through human freedoms. AI accountability significantly mediates the relationship between human freedoms and the mobile index. This has implications for the empowering of users in the design and use of mobile health applications.

Theoretical Background

HUMAN FREEDOMS

Capability model view human freedoms as a means to achieve the lives people choose to live[1]. He states: “human rights are best seen as rights to certain specific freedoms, and that the correlate obligation to consider the associated duties must also be centered around what others can do to safeguard and expand these freedoms. Since capabilities can be seen, broadly, as freedoms of particular kinds, this would seem to establish a basic connection between the two categories of ideas.”[1(p2)] In this regard, social sustainability is vital due to its impact on health and safety, with a focus on wellbeing, fairness, and resource distribution. These include access to basic needs, social justice, equity, human rights, health, and safety. In healthcare, social sustainability involves creating accessible, integrated, equitable communities, and addressing the needs of the health and well-being of users. Maghsoudi et.al. emphasize[7] the role of collaborative networks in enhancing social sustainability within healthcare systems using a conceptual framework consisting of six propositions. The first proposition high-lights the importance of collaboration between healthcare professionals and patients, enhancing patient wellbeing and satisfaction.

The second aspect of human freedoms in health which focuses on inter- professional collaboration among healthcare providers, improving care quality and professional satisfaction. The third proposition emphasizes collaboration among scientists, leading to innovative treatments and better patient care. In the fourth proposition, collaboration involving healthcare managers, policymakers, and professionals is seen as key to implementing effective, socially sustainable healthcare policies. The fifth proposition advocates for inter-organizational collaboration among healthcare entities to enhance service quality and resource availability. Finally, the sixth proposition underscores the collaboration among healthcare professionals, scientists, and suppliers, aiming to improve treatment methods and service accessibility, contributing to the overall social sustainability of healthcare systems. Overall, they underscore the potential of collaborative networks in healthcare to enhance social sustainability, emphasizing their role in achieving better patient outcomes, increased satisfaction, and equitable resource distribution. Medina & Sole-Sedeno explore[8] the transformation of the Mediterranean diet from a mid-20th century health-centric model to a symbol of cultural and historical significance, a shift highlighted by its UNESCO recognition as an "Intangible Cultural Heritage of Humanity."

In the context of human freedoms, the broader implications of health information technologies are explored in studies by Sieck et al, Medina & Sole-Sedeno and Seth et al.[3,8,9] Seth et al.'s discussion[9] on decolonizing global health research through web-based platforms, especially in the context of India, emphasizes the empowering potential of internet-based tools in promoting equitable research practices and local community participation. In contrast, Medina & Sole Sedeno highlight[8] the cultural and environmental impacts of the global popularization of the Mediterranean diet, suggesting a multidisciplinary approach to preserve its holistic significance. Masiero and Bailur delve[10] into the social consequences of digital identity systems, advocating for an inclusive, justice-oriented approach, particularly for vulnerable groups like migrants and informal workers. This perspective is crucial in understanding the broader implications of digital technologies in societal contexts.

Medina & Sole-Sedeno explore[8] the transformation of the Mediterranean diet from a mid-20th century health-centric model to a symbol of cultural and historical significance, a shift highlighted by its UNESCO recognition as an "Intangible Cultural Heritage of Humanity." The explanation constructs a narrative around the diet's evolution, examining the risks of global popularization that could detach the diet from its cultural roots and cause environmental imbalances. The study stresses that preserving the Mediterranean diet's holistic significance requires a multidisciplinary perspective, integrating its social, cultural, and sustainability aspects to maintain its relevance in modern contexts.

Digital technologies such as mHealth technologies, while promising in addressing health disparities, have complex interactions with the social determinants of health (SDOH) that need careful consideration. They offer a means of attaining digital inclusion through access to SDOH resources. Studies by Rogers et al. and Ye & Ma illustrate[4,5] this interaction vividly. Rogers et al. focus[4] on integrating mHealth with SDOH in maternal health, using human factors/ergonomics (HF/E) frameworks to explore solutions like improved transportation access to healthcare services. This approach underscores the potential of mHealth in practical applications, particularly in community-based settings. This means that human freedoms include the following SDOH: ability to access an education or achieve literacy, health, location, healthcare access; Reproductive, Maternal and Child Health (RMCH); Water, Sanitation and Hygiene (WASH). The integration of artificial intelligence (AI) into healthcare systems, particularly through mobile health (mHealth) applications, brings both challenges and opportunities in preserving and enhancing these freedoms. As AI technologies advance, they hold immense potential to improve healthcare delivery by personalizing care, enhancing diagnostic accuracy, and facilitating more efficient management of health resources.

DIGITAL INCLUSION

Digital inclusion encompasses efforts to guarantee that everyone has equal opportunities to access and utilize information and communication technologies. Digital inclusion is needed for mobile health applications to be able to address the needs of people in low resource communities to stay healthy. This concept involves providing affordable Internet service, making Internet-enabled devices available, offering digital literacy training, ensuring quality technical support, creating mobile applications, online content aimed at fostering independence, community engagement, and collaboration. These elements lay the groundwork for integrating mobile technology into healthcare delivery[3]. Digital technologies like Mobile health (mHealth) technologies, while promising in addressing health disparities, have complex interactions with the SDOH that need careful consideration. mHealth technologies offer a means of attaining digital inclusion through access to SDOH resources. Studies by Rogers et al. and Ye & Ma[4,5] illustrate this interaction vividly. Rogers et al. focus[4] on integrating mHealth with SDOH in maternal health, using human factors/ergonomics (HF/E) frame- works to explore solutions like improved transportation access to healthcare services. This approach underscores the potential of mHealth in practical applications, particularly in community-based settings. Similarly, Ye and Ma's study sheds[5] light on how wearable devices and smartphone apps impact physical activity, highlighting the influence of SDOH such as age, gender, and income on technology adoption. Both studies point towards the need for mHealth solutions to be tailored to specific community needs and social contexts, suggesting that technology alone is not a panacea but part of a broader, more holistic approach to health.

Digital inclusion seen to be attained through use of mobile health applications and are becoming ubiquitous as people look for resources, they need to stay healthy.

Mobile health, commonly known as mHealth, involves leveraging mobile devices to foster healthier habits and self-learning. mHealth is broadly defined by the World Health Organization (WHO)[11] as medical and public health practices supported by mobile and wireless technologies, including phones, Personal Digital Assistants (PDAs), and patient monitoring devices. As Internet connectivity and smart/mobile device usage have increased, there's a growing interest globally in enhancing the availability and effective implementation of mHealth to better healthcare services and, in turn, the overall health of communities. This paper aims to study the effects of Digital inclusion on human health and explores its role in mHealth applications.

ALGORITHMIC BIAS

In the field of healthcare, the usage of Artificial Intelligence (AI) to improve clinical decision-making and outcomes is not free from the risks of algorithmic biases. Maintaining AI accountability in healthcare is critical because AI systems can inadvertently perpetuate existing disparities through algorithmic bias, data-driven bias, and data gap bias. Data-driven bias occurs when the datasets used to train AI systems do not accurately represent the diversity of the population (Norori et al., 2021). This lack of representation in the dataset as it might not be diverse enough for analysis which will lead to AI systems that perform well for majority groups but poorly for minority groups, potentially impairing research with health disparities. For example, if a training dataset predominantly consists of data from one racial group, the AI's diagnostic accuracy might be lower for other racial groups not well represented in the training data.

Algorithmic bias is a type of bias that is introduced by the algorithms themselves, it is possible due to the way data is processed or the specific models used[12]. These algorithms might amplify existing inequalities by perpetuating or even exacerbating biases present in the training data. Finally, data gap bias arises when important data is missing altogether, which can skew results in the AI predictions and lead to misdiagnoses or inappropriate treatment plans. This kind of bias is particularly dangerous as it can lead to systematic neglect of certain groups within the healthcare system, such as women, the elderly, or those from lower socio-economic backgrounds, who are often underrepresented in clinical trials and other medical research that feeds AI development.

Understanding of bias that exist in the algorithms can enable better healthcare provision. Bias in AI can arise due to training data used to train algorithm (Data bias) and algorithmic bias that can exist due to the design of the algorithm[13]. Bias in health care exist due to nature of human interactions and decision-making process[13]. Flecther and others[14] mention in research about bias and fairness in global health that fairness can be considered at two levels, individual and group level. An algorithm can be customized to provide decisions for individuals when providing treatments if the individuals share similar characteristics[14]. Group fairness in the context of machine learning and AI is a concept that aims to ensure that algorithms make decisions or predictions without systematic bias or discrimination against specific demographic groups defined by characteristics such as race, gender, or socioeconomic status[14]. It involves evaluating the performance of AI models across different groups to ensure that no group is unfairly disadvantaged or favored by the algorithm. The goal is to achieve equitable outcomes for all groups, taking into account the biological, physiological, and social variations that may exist among different populations.

Addressing these biases involves adopting rigorous methodologies for data collection, algorithm design, and continuous evaluation to ensure AI systems perform fairly across diverse populations. Engaging in open science practices, such as sharing data and methodologies openly and ensuring diverse participation in AI development, can help mitigate these biases[12]. Furthermore, implementing strategies like algorithmic auditing, where AI systems are regularly checked for biases and their potential impacts on different demographics, can foster equitable AI outcomes. As AI technologies continue to integrate into the healthcare system, the demand grows to address these biases proactively for practical implementation of AI in providing equitable health access and outcomes for all.

ALGORITHMIC ACCOUNTABILITY

Accountability of artificial intelligence (AI) algorithms needs to address the bias in many forms has entered the lives of people all over the world. This bias is reflected in legal, medical and even purchasing decisions are supported by recommender systems that draw upon different types of data located in multiple servers running on cloud computing systems. Financial systems, including those powered by blockchain, have machine learning. Electronic equipment, appliances, cars and even simple gadgets are being given machine learning capabilities, some with location-based AI tools. While the location of the data being fed into artificial intelligence engines may not be easily traced, the people who unknowingly offer their data are very much in the eye of the intelligent machine. This data is harvested from users all over the world and fed into Artificial Intelligence systems. These systems use machine learning that can in simple terms be generative or descriptive. Generative machine learning algorithms use existing content, through unsupervised learning, to generate original artifacts that look real. For example, generative machine learning is used for conversation agents, creation of new artwork like nonfungible tokens or NFTs, images of people and even academic articles[6,15].

Accountability of AI technology is set to deeply influence how content is produced and created. Key developments like ChatGPT and DALL-E have been instrumental in the rising prominence of generative AI in the 21st century. ChatGPT, a generative AI-powered chatbot, crafts responses that mimic human speech based on its training. In a similar vein, DALL-E uses textual prompts to create lifelike images, showcasing another facet of generative AI). These innovations are reshaping our understanding of content creation[16]. Recent advances in AI techniques and Machine Learning algorithms have offered retailers using digital assistants for customer service higher satisfaction Healthcare applications in precision medicine and drug discovery use ML approaches as a powerful and efficient way to use large amounts of data generated from modern drug discovery to model small molecule drugs, gene biomarkers and identifying the novel drug targets for various diseases[6].

With advent of ChatGPT and other generative Artificial Intelligence (AI), the integration of AI into various systems across industries is underway. Machine Learning (ML) is very well-known applications of AI that is being employed in to understand large enough data sets that comprise variety of data from various data sources in various data types. AI technology in the mHealth has to deal with clinical data, prescription data, MRI scans, CT images, insurance data, laboratory data are illustrated in studies on AI in mHealth applications and its effectiveness handling medical problems. According to Larburu et al., AI based mHealth application[17] for avoiding heart failures in patients, doctors are using simple ML methods for generating alerts in the identification of heart failure. The application of Naïve Bayes classifier in the methodology to identify the heart failure has reduced the false alerts from 28.64 to 7.8 patients. This system has made forecasting of possible risk of heart failure and more possibility of a heart failure among the patients and deliver alert via mHealth application.

Wieringa's research clarifies[18] the complexities of algorithmic accountability, presenting it as a multifaceted responsibility that includes the entire network involved in the socio-technical systems of algorithms. This framework insists on the necessity for all parties involved—ranging from decision-makers and developers to users—to actively engage in the explanation and justification of the design, implementation, and impact of these systems[18]. Essentially, this approach underlines the critical need for a transparent understanding among stakeholders regarding their roles and responsibilities within the algorithmic ecosystem, highlighting the importance of delineating accountability across various dimensions of the algorithm's lifecycle. Furthering this discourse, Horneber et al. dissect[19] accountability into social, institutional, organizational, and technical domains, advocating for governance and ethical development measures in machine learning (ML) systems. This entails a commitment to fairness and transparency in algorithmic decision-making to prevent bias and ensure equitable outcomes. In a similar vein, Bruno Lepri and colleagues champion[20] the concept of Open Algorithms (OPAL), advocating for a participatory approach in the development and evaluation of algorithms to safeguard their transparency and fairness. They suggest the utilization of transparent and fair ML models, alongside rigorous auditing and interdisciplinary collaboration, as vital strategies for embedding accountability within algorithmic systems. The discourse on algorithmic accountability is thus revealed as a complex, multidimensional challenge that necessitates clear definitions, robust frameworks, and strategic measures to navigate the ethical dimensions of algorithms and secure their responsible use.

There appears to be a role of AI in mobile health applications is becoming pervasive. Vandelanotte et al. propose[21] a novel approach to mHealth interventions using machine learning for real-time personalization. Their study highlights the integration of various data sources and the use of a likable digital assistant, demonstrating the potential of AI in health behavior change. Han et al. introduces[22] a novel method to extract SDOH information from electronic health records using deep learning-based NLP. This approach emphasizes the importance of identifying a comprehensive set of SDOH in clinical practice, underscoring the potential of advanced analytics in healthcare. People suffering from health issues facing poverty tend to suffer from algorithmic bias. Artificial intelligence models tend to have difficulty in representing human behavior. Yet they carry out tasks that can be carried out by trained professionals. For example, radiologists who are trained to screen X-rays are being replaced by AI engines that can detect cancer at rates that are more accurate than the human radiologists they replace.

A predictive mathematical model is as seductive in its elegance as it is dangerous when powering an artificial intelligence application. Despite the exponential growth and precision of machine learning algorithms over the past thirty years, one thing remains the same: little is known about how the models arrive at their predictions. No matter how accurate the answers, the decision-making processes used by the machine learning algorithms remain elusive[15]. The decision making of the AI solutions have a need to provide accountability and transparency in their decision making. Lepri et al propose[20] the use of Open-source Algorithms to ensure fairness and transparency.

Apart from the above-mentioned studies on AI in mHealth applications there are few more studies that are worth looking at like Sangers et al. study[23] on skin cancer risk assessments using mHealth consumer apps that are integrated with deep learning and Xu et al. study[24] on the precision medicine points out that AI/ML has rapidly evolved precision medicine through designing, analyzing treatment, and prevention strategies to subject's unique characteristics.

Conceptual Model

The above studies suggest that human freedoms are important for digital inclusion. It also appears that algorithmic accountability mediates the relationship between human freedoms and the ability of people to access the resources they need to stay healthy though their mobile phones. This accountability in algorithmic bias can be measured in terms of Health Inequality; Multidimensional Poverty Index and the HDI when understanding digital inclusion. AI accountability is measured in terms bias that potentially renders an AI algorithm unfair and non-transparent; which includes, data-driven bias, data gap bias, lack of data standards and data interoperability. An illustration of the conceptual model is presented below:

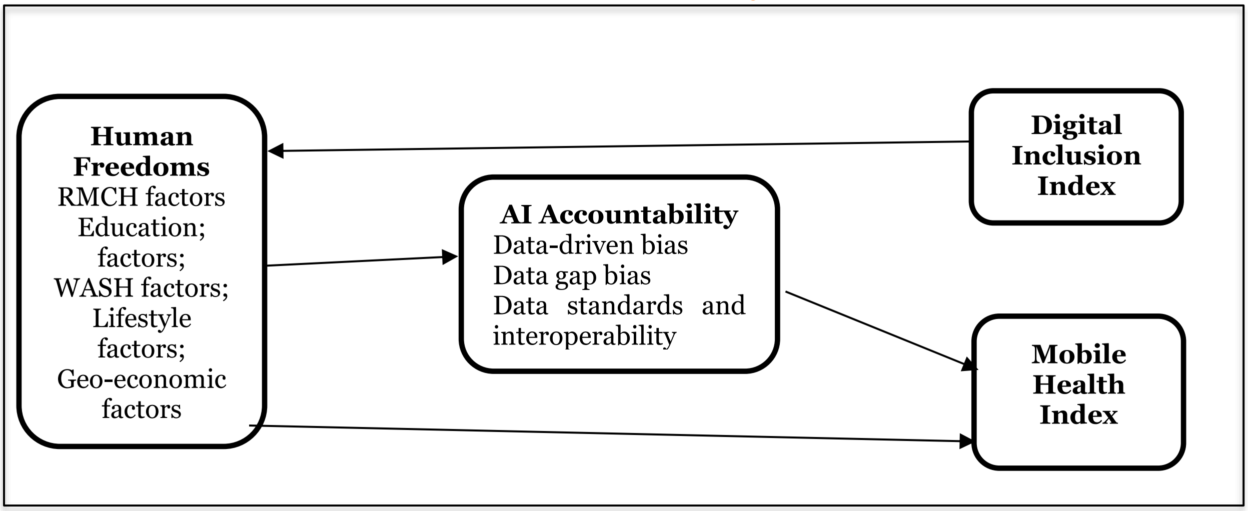

Figure 1: Conceptual Model

Human freedom variables are classified in 5 categories: 1) Reproductive, Maternal and Child Health (RMCH) factors: Infant mortality rate, under-5 mortality rate, healthcare delivery, Composite Coverage index, healthcare access, healthcare facility without access to hygiene, sanitation and water services. 2) Education factors: Literacy rate and post-secondary educational attainment. 3) Water, Sanitation and Hygiene (WASH) factors: Population using unimproved sanitation services, Population using unimproved water services, and population with no hygiene services. 4) Geo-economic factors: Employment-population ratio, unemployment rate, coverage of unemployment benefits, social insurance program, labor force participation, proportion of population in poorest wealth category. Lifestyle factors: Physical inactivity, alcohol dependence, and alcohol use disorder.

Given our conceptual model, three measures were used to quantify AI accountability: Data-driven bias of AI, Data gap bias of AI, and Data standards and interoperability in AI. These measures of AI bias were elaborately described[12] by Norori et. al., in their study, where they examined how a measure of access to public datasets can be used to quantify bias in AI; since the level of access and quality of publicly available datasets indirectly impacts the fairness of algorithms trained and developed based on these datasets[12]. Hence, we propose that a country with limited and poor public data access can potentially be affected by algorithmic bias, for any algorithm trained and developed based on those publicly available datasets.

Based on the above conceptual model for this study, the 2 dependent variables for this study are 'Digital Inclusion Index' and 'Mobile Health Index'. The Digital Inclusion Index was derived as an average of 4 variables indicating access to mobile, computer and the internet as follows:

Digital Inclusion Index:

$$\frac{\text{Internet} + \text{Mobile Wireless} + \text{Mobile Subscription} + \text{Computer Usage}}{4}$$

The mobile health index is derived as an average of variables that indicate access to mobile devices, internet and the HDI health component.

Mobile Health Index:

$$\frac{\text{Internet} + \text{Mobile Wireless} + \text{Mobile Subscription} + \text{HDI (Health Component)}}{4}$$

As illustrated in the above model, the following null hypotheses are tested:
H1: There is no significant relationship between human freedom and digital inclusion.
H2: There is no significant relationship between human freedom and accountability.
H3: There is no mediating effect of accountability on the relationship between human freedom and mobile health.

The following section explains the methodology used to test the above hypotheses.

Methodology

In order to test the model, the study employs an analytical cross-sectional design where data at a given period is collated from secondary sources and analyzed, as described in a study by Xiaofeng and Zhenshun[25]. The data used are already collated for public access by reliable sources including the World Bank Database, WHO metadata portal, United Nations Development Programme (UNDP) data portal and International Telecommunication Union (ITU). Dataset across these sources were available at country levels, for the most recent year (2023). After taking care of missing records and pre-processing of the combined dataset, the result from this study was based on data from 169 countries across the globe.

All digital inclusion variables were sourced from the ITU DataHub, while other variables were sourced from 8

WHO Metadata. The metadata includes: Global Burden of Diseases; Global Health Observatory; Health Determinants (DHS & World Bank); Healthcare Access; Reproductive, Maternal and Child Health; Water, Sanitation and Hygiene; Health Inequality; Multidimensional Poverty Index.

Specifically, the AI accountability measures were exported from the World Bank data portal of the complete Statistical Performance Indicator (SPI) measures with all its relevant dimensions and pillars. This study used data on the 5 pillars of SPI, including Data Use, Data Service, Data Product, Data Source and Data Infrastructure. To incorporate these pillars into our study, we developed the following:

Data-driven bias: Average of the Data Use and Data Service scores

Data gap bias: Average of the Data Service, Data Product and Data Source scores

Data standards and interoperability: Average of the Data Service and Data Infrastructure scores.

The independent variables, generally termed 'Human Freedom Determinants', include: Reproductive, Maternal and Child Health Factors (RMCH), Educational Factors, Geo-economic/Location Factors, Lifestyle Factors, and Water, Sanitation and Hygiene Factors (WASH). The derivation of each of the 5 independent variables was performed using a principal component analysis (PCA) as a dimension reduction method and evaluation technique. This helps in reducing number of variables to be regressed with each of the outcomes, while retaining the most important information in each category. The PCA decorrelated the original variables into a set of newly uncorrelated and scaled variables, known as principal component, for each of the 5 categories. Hence, the principal components (RMCH, Educational, Geo-economic, Lifestyle, and WASH) are derived scores ranging on a scale of 0 – 100. The entire PCA methodology was performed using the decomposition and MinMaxScaler functions from the sklearn library on Python. Three indices were used as mediators between the 5 independent variables and each of the dependent variables. The mediators, termed as the 'AI Accountability' variables, include AI data-driven bias, AI data-gap bias, and AI data standards. A summary of variables in each of the 5 categories of independent variables is presented in the table below:

Categories	***Variables***	***Definition***
RMCH factors *(Lower scores indicate better RMCH index)*	Infant mortality rate	Mortality rate between birth and 11 months per 1000 live births (WHO, 2023).
	Under-5 mortality rate	Mortality rate between birth and before age of 5 years per 1000 live births (WHO, 2023).
	Healthcare delivery	Proportion of women with child delivery at a healthcare facility (WHO, 2023).
	Composite Coverage Index	"The composite coverage index is a weighted score reflecting coverage of eight RMNCH interventions" (WHO, 2023)
	Healthcare access	Estimate of the population having problems with healthcare access; owing to transportation, permission, financial, proximity, lack of company, or ignorance (WHO, 2023).
	Healthcare facility with no hygiene, sanitation and water services	Proportion of healthcare facilities with no hygiene, sanitation or water services (WHO, 2023)
Education factors *(Lower scores indicate better education index)*	Literacy rate (Adult)	Proportion of adults, 15+ years, who are literate.
	Post-secondary educational attainment	Proportion of adults, 25+ years, who completed at least post-secondary education (World Bank, 2023).
Geo-economic factors *(Higher scores indicate better geo-economic index)*	Employment to population ratio	Ratio of the employed population and total population (WHO, 2023)
	Unemployment rate	Percentage of the total labor force who are unemployed (World Bank, 2023).
	Coverage of unemployment benefits	Percentage of population receiving unemployment benefits due to labor market reasons (World Bank, 2023).
	Social insurance program	Percentage of population receiving benefits from the social insurance program (World Bank, 2023).
	Labor force participation	Percentage of working-age population who are currently active in the labor force (UNICEF)
	Poorest category	Estimate of the population percentage in the poorest wealth quintile (DHS).
Lifestyle factors *(Higher scores indicate better lifestyle index)*	Physical inactivity	Prevalence of insufficient physical activity among adults and adolescents (WHO, 2023).
	Alcohol dependence	Proportion of population, 15+ years, who reported alcohol dependence over past 12-months (WHO, 2023).
	Alcohol use disorder	Proportion of population, 15+ years, who reported alcohol use disorders over past 12-months (WHO, 2023).

Categories	Variables	Definition
WASH factors *(Higher scores indicate better WASH index)*	Population using unimproved sanitation services	Proportion of population with unimproved sanitation services (WHO, 2023)
	Population using unimproved water services	Proportion of population with unimproved water services (WHO, 2023)
	Population with no hygiene services	Proportion of population with no hygiene services (WHO, 2023)

Table 1. Description of Human Freedom Determinants

With a view to testing the hypothesis earlier stated, two major statistical techniques were used – the Pearson Product Moment Correlation and the Regression Analysis. For hypothesis 1 and 2, the correlation analysis was performed to determine the strength of the relationship between human freedom and the 2 outcome variables (digital inclusion and mobile health), as well as the 3 mediators (AI data-driven bias, AI data-gap bias and AI data standards). For these two hypotheses, the linear regression analysis was carried out to quantify the measure of the observed relationship. To test hypothesis 3 and 4, the linear regression analysis was conducted in phases, to obtain the difference in the statistical significance of human freedom variables with mediators and without mediators. A statistical significance level of 5% was used in determining factors considered to be significant.

Results

The correlation between the human freedom determinants and digital inclusion showed that four of the determinants had a statistically significant correlation with digital inclusion index; RMCH factors (r = -0.58), educational factors (r = -0.59), lifestyle factors (r = -0.39) and WASH factors (r = 0.64). The table below shows the regression analysis of each of the 4 human freedom determinants on digital inclusion index. From the result, it was evident that digital inclusion index was a statistically significant predictor for RMCH, educational, lifestyle and WASH factors. Notably, a unit increase in the digital inclusion index reduces the indices of RMCH and education by 0.56 and 0.48, respectively. Thus, suggesting that higher levels of digital inclusion index improve both the reproductive, maternal and child health indicator and the education indicator. In terms of the lifestyle factors, a unit increase in digital inclusion index reduces the indicator by 0.53. Conversely, a unit increase in digital inclusion index increases the WASH indicator by 0.95. Hence, the result suggests that higher levels of digital inclusion index diminish the lifestyle factors of individuals, but improves their WASH factors. This is illustrated in table 2 below:

Reproductive, Maternal and Child Health Factors			**Educational Factors**		
	β	p-value		β	p-value
Intercept	52.73	< 0.001	Intercept	56.09	< 0.001
Digital Inclusion Index	−0.56	< 0.001	Digital Inclusion Index	−0.48	< 0.001
Lifestyle Factors			**Water, Sanitation and Hygiene Factors**		
	β	p-value		β	p-value
Intercept	69.95	< 0.001	Intercept	−2.90	0.688
Digital Inclusion Index	−0.53	< 0.001	Digital Inclusion Index	0.95	< 0.001

Table 2. Regression Analysis of Human Freedom Determinants on Digital Inclusion Index

The correlational analysis showed that all human freedom determinants, except geo-economic factors, had a statistically significant relationship with mobile health index. The mediating variables – multidimensional poverty index and human development index were also significantly correlated with the mobile health index.

Results from the pairwise correlation analysis between all four human freedom variables (RMCH, education, ge0-economic and WASH) and all three AI accountability variables (AI: Data-driven bias, Data gap bias, and Data standards and interoperability) showed that RMCH (r = -0.56), geo-economic (r = -0.34) and WASH (r = -0.52) had a statistically significant correlation with AI data-driven bias, at 5% level. Similarly, all three variables – RMCH (r = -0.62), WASH (r = -0.56), and geo-economic (r = -0.37) – showed a statistically significant relationship with AI data gap bias. Lastly, in like manner, the same set of human freedom variables had a significant relationship with AI data standards and interoperability. Essentially, the result revealed RMCH factors had the strongest negative relationship with all three AI accountability variables; WASH factors also consistently showed a strong negative relationship with the three AI accountability variables; a negative but weak relationship was observed between geo-economic factors and each of the 3 AI accountability variables; educational factors did not exhibit a significant relationship with any of the AI accountability variables, and the observed relationships with each of the AI accountability was very weak. Hence, all human freedom variables, with the exception of educational factors, were included in the regression model against AI accountability.

The regression analysis of AI accountability on human freedom, shown in the table below, revealed that RMCH and WASH factors individually had a significantly negative effect on all three AI accountability measures. While the other human freedom variables are held constant, the effect of geo-economic on AI accountability was positive, but the effect was not significant for AI data-driven bias. Since each of our AI accountability variable measures level of biasedness, unfairness and lack of transparency, thus, our result suggests that improvement in both RMCH and WASH conditions potentially reduces AI biasedness and unfairness; for instance, an increase in RMCH factors by one unit collectively reduces lack of data standards by 0.55, AI data gap bias by 0.44, and AI data-driven bias by 0.38; a unit increase in WASH factors lowers AI data-driven bias by 0.16, AI data gap bias by 0.13, and lack of data standards by 0.19. While the other variables (RMCH and WASH) are kept constant, geo-economic factors did not seem to improve AI accountability; for instance, geo-economic factors did not significantly affect AI data-driven bias, but had a marginally positive significant effect on AI data gap bias and lack of data standards. This is illustrated below in table 3:

	Human Freedom and AI Data-drive bias ($R^2 = 0.3499$; $p = < 0.001$)		**Human Freedom and AI Data-gap bias ($R^2 = 0.4218$; $p = < 0.001$)**		**Human Freedom and AI Data-standards and interoperability ($R^2 = 0.4188$; $p = < 0.001$)**	
	β	**p-value**	β	**p-value**	β	**p-value**
Intercept	51.67	< 0.001	63.52	< 0.001	72.48	< 0.001
RMCH factors	-0.38	< 0.001	-0.44	< 0.001	-0.55	< 0.001
Geo-economic factors	0.14	0.066	0.15	0.024	0.19	0.040
WASH factors	-0.16	0.004	-0.13	0.006	-0.19	0.004

Table 3: Regression Analysis of AI accountability on Human Freedom variables

In explaining the relationship between human freedom variables and mobile health index, a correlational analysis confirmed that RMCH factors had the strongest relationship with mobile health index (r = 0.82). Geo-economic and WASH factors also had a positively strong relationship with mobile health (r = 0.71 and 077, for ge0-economic and WASH respectively). A weak relationship was observed between educational factors and mobile health index (r = 0.27). All of the four human freedom variables appeared to have had a statistically significant relationship with mobile health index, at 5% level. Hence, all human freedom variables were introduced in the regression model.

The regression analysis further confirmed RMCH, geo-economic and WASH factors all had significant effects on mobile health. A unit increase in the RMCH factors potentially improves mobile health index by 0.44; a similar increase in geo-economic factors improves mobile health index by 0.21; increase in WASH factors by a unit also increases mobile health by 0.18. This is illustrated in table 4 below:

	Human Freedom and Mobile Health Index ($R^2 = 0.7542$; $p = < 0.001$)	
	β	**p-value**
Intercept	14.53	< 0.001
RMCH factors	0.44	< 0.001
Educational factors	-0.07	0.090
Geo-economic factors	0.21	< 0.001
WASH factors	0.18	< 0.001

Table 4: Regression Analysis of Mobile Health on Human Freedom variables

To evaluate the mediating effect of AI accountability on the relationship between human freedom variables and mobile health, we at first considered if there is some correlation between AI accountability measures and mobile health. Result (Figure 1) showed that all 3 AI accountability variables had a statistically significant negative correlation with mobile health; AI data-driven bias (r = -0.55), AI data gap bias (r = -0.53), and lack of data standards (r = -0.62).

To evaluate the mediating effect of AI accountability on the relationship between human freedom variables and mobile health, we at first considered if there is some correlation between AI accountability measures and mobile health. The results shown in Figure 2, indicate that all 3 AI accountability variables had a statistically significant negative correlation with mobile health; AI data-driven bias (r = -0.55), AI data gap bias (r = -0.53), and lack of data standards (r = -0.62).

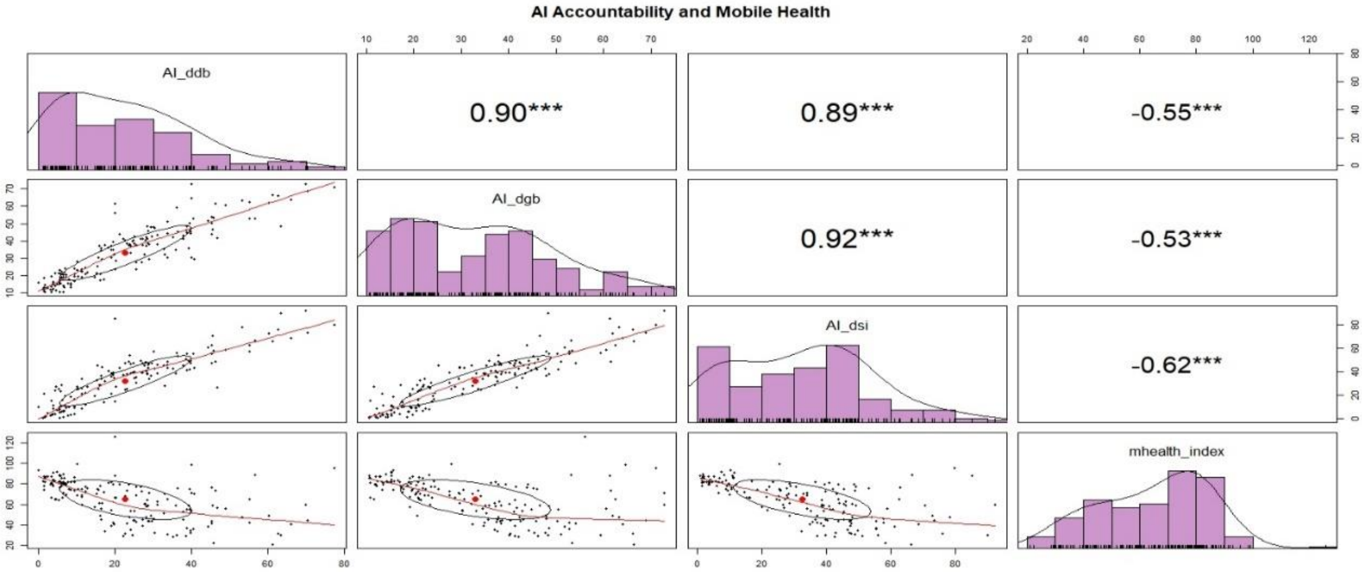

Figure 2: Correlation Analysis of AI Accountability and Mobile Health

The regression analysis below shows the magnitude of the mediating effect of AI data-driven bias on the relationship between human freedom variables and mobile health. From the result, we found that all of the human freedom variables were still statistically significant despite the inclusion of AI data-driven bias, as a mediator. And data-driven bias was also found to have a statistically significant effect in the same model. Importantly, the result from this model also showed that an increase in all of the human freedom variables potentially leads to an improvement in mobile health; conversely, an increase in AI data-driven bias reduces the level of mobile health index. The adequacy of this model, measured by the r-squared, confirmed that up to 80% of the variation in mobile health index was explained by the three human freedom variables (RMCH, geo-economic and WASH) and AI data-driven bias.

Thus, from the result, we infer that AI data-driven bias only has a partial mediation effect on the relationship between human freedom and mobile health. A look at the average causal mediation effect (ACME) for AI data-driven bias confirmed that the observed mediation effect cannot be considered to be statistically significant. This is illustrated in table 5 below:

	AI Data-driven bias and Human Freedom ($R^2 = 0.3499$; $p = < 0.001$)		**Mobile Health Index and Human Freedom: mediated by AI Data-driven bias** ($R^2 = 0.8034$; $p = < 0.001$)		
	β	**p-value**		β	**p-value**
Intercept	51.67	< 0.001	**Intercept**	17.93	< 0.001
RMCH factors	-0.38	< 0.001	**RMCH factors**	0.43	< 0.001
Geo-economic factors	0.14	0.066	**Geo-economic factors**	0.16	< 0.001
WASH factors	-0.16	0.004	**WASH factors**	0.15	< 0.001
			AI data-driven bias	-0.12	0.016

Table 5: Mobile Health Index and Human Freedom, mediated by AI data-driven bias

The table below shows how much of a mediation effect AI data gap bias has on the relationship between human freedoms and mobile health. This result revealed all human freedom variables remained statistically significant, despite the introduction of AI data gap bias in the model. Although, data gap bias was not statistically significant in this model, the overall model adequacy showed that up to 80% of the variation in mobile health index was explained by all four variables included in the model. Notably, similar to the previous result, an improvement in the level of the human freedom variables brings about improvement in the level of mobile health index; while mobile health index drops as the level of AI data gap bias increases.

Since the human freedom variables remained statistically significant but AI data gap was not significant in the same model, we can infer that there is no mediation effect of AI data gap bias on the relationship between human freedoms and mobile health. This is also confirmed by the ACME result (Table 8), that showed none of the ACME for the AI data gap bias was statistically significant. Hence, we can conclude no statistically significant mediation effect exists in this model.

	AI Data gap bias and Human Freedom ($R^2 = 0.4218$; $p = < 0.001$)		Mobile Health Index and Human Freedom: mediated by AI Data gap bias ($R^2 = 0.8034$; $p = < 0.001$)		
	β	p-value		β	p-value
Intercept	63.52	< 0.001	**Intercept**	18.84	< 0.001
RMCH factors	-0.44	< 0.001	**RMCH factors**	0.43	< 0.001
Geo-economic factors	0.15	0.024	**Geo-economic factors**	0.15	0.001
WASH factors	-0.13	0.006	**WASH factors**	0.16	< 0.001
			AI data gap bias	-0.11	0.058

Table 6: Regression Analysis: Mobile Health Index on Human Freedom, mediated by AI data standards and interoperability

The result below shows the level of mediation effect from lack of AI data standards on the relationship between human freedom and mobile health. We found that all of the human freedom variables were still statistically significant following the introduction of AI data standards. The r-squared from this model suggests these set of variables explained up to 80.4% of the variation in mobile health index. Similar to previous results, improvement in the level of all human freedom variables drives mobile health index in upward direction, while an increase in lack of AI data standards leads to reduced mobile health index.

Since all of these variables (human freedom and lack of AI data standards) are statistically significant, the result suggests there is only an observed partial mediation effect from AI data standards on the relationship between human freedom and mobile health. Lastly, results of the ACME for this model showed that, the observed mediation effect from AI data standards is not statistically significant. Thus, we conclude that there is no significant mediation effect in this model. This is illustrated in table 7 below:

	AI Data standards and Human Freedom ($R^2 = 0.4188$; $p = < 0.001$)		Mobile Health Index and Human Freedom: mediated by AI Data standards ($R^2 = 0.8041$; $p = < 0.001$)		
	β	p-value		β	p-value
Intercept	72.48	< 0.001	**Intercept**	19.28	< 0.001
RMCH factors	-0.55	< 0.001	**RMCH factors**	0.42	< 0.001
Geo-economic factors	0.19	0.040	**Geo-economic factors**	0.16	< 0.001
WASH factors	-0.19	0.004	**WASH factors**	0.15	< 0.001
			AI data standards	-0.10	0.011

Table 7: Regression Analysis: Mobile Health Index on Human Freedom, mediated by AI data standards and interoperability

Based on results from the regression models evaluating the mediation effects of each of the AI accountability variables, we can conclude that AI accountability does not mediate the effects of the relationship between human freedom and mobile health index. Rather, AI accountability (in terms of AI data-driven bias, AI data gap bias and lack of AI data standards) have significantly direct effects on mobile health. Essentially, with the inclusion of AI accountability variables in the regression model explaining mobile health, we found that AI accountability had the most contribution in each of these models; increasing the r-squared by approximately 40% in any of the 3 models. Thus, our results confirmed that AI accountability should be considered a key factor in explaining, predicting and describing mobile health index. This is illustrated in the table below:

	AI data-driven bias		AI data-gap bias		AI Data standards and interoperability	
	$ACME$	p-value	$ACME$	p-value	$ACME$	p-value
RMCH factors	0.048	0.160	0.046	0.190	0.057	0.140
Geo-economic factors	-0.016	0.192	-0.012	0.280	-0.020	0.104
WASH factors	0.017	0.180	0.015	0.200	0.020	0.100

Table 8: Mediation Effect of AI Accountability on Mobile Health Index and Human Freedom Factors

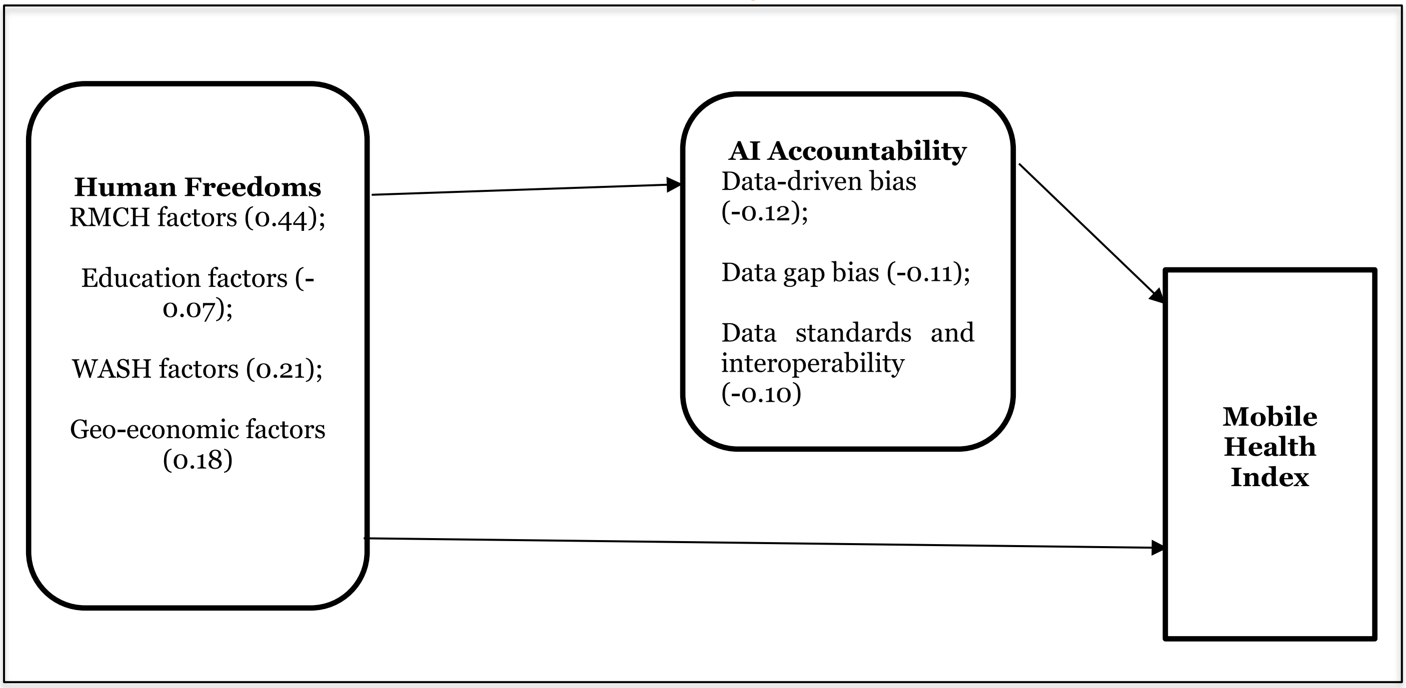

Figure 3: Relationship between Human Freedoms and Mobile Health, mediated by Mobile Health Index

Discussion

The first research question seeks to find out how human freedoms effect digital inclusion and mobile health; our study confirmed that digital inclusion enhances human freedoms and, in turn, human freedoms are essential in enabling mobile health. The second research question exposed that four of the human freedom variables (RMCH factors, geo-economic factors, and WASH factors) had a statistically significant effect on mobile health index; educational factors only had a marginal effect on mobile health index. Similarly, the same set of human freedom variables had a statistically significant effect on each of the 3 AI accountability variables (AI data-driven bias, AI data-gap bias, and AI data standards). This brings clarity to the importance of the role of human freedom variables on both AI accountability and mobile health index. On the last research question, our study confirmed that none of the 3 AI accountability variables had a significant mediating effect on the relationship between human freedoms and mobile health. This essentially illuminates the idea that AI accountability on its own can directly impact mobile health index; as seen in our results, across the 3 models developed, the coefficient of determination (R^2) increased by at least 40% when any of the accountability variables in included in the regression model explaining the relationship between human freedoms and mobile health.

Given all three mediating variables – AI data-driven bias, AI data-gap bias, and AI data standards – were found to be significantly correlated with the mobile health index. The result from this study also suggests that AI accountability has an effect on the ability of people to stay healthy using their mobile applications. Human freedom is important as people suffering from health issues facing poverty tend to suffer from algorithmic bias. The findings in the paper offer a means of conceptualizing algorithmic bias in a way that empowers both the users and developers of mobile health applications with the freedom and ideology to interact with the applications to their personal preferences, while considering external factors (human freedom) capable of inhibiting or promoting their access to healthcare.

To be more specific, a user of a given mobile health application can understand that the RMCH (reproductive, maternal and child health) factors, educational factors, geo-economic factors, and WASH (water, sanitation and hygiene) factors can limit or enhance their freedom to gain access to healthcare services through mobile health. Simultaneously, developers of mobile health applications become aware that the quality of data use and services can be a driver for bias in data used in developing an AI algorithm; the quality of data services, data products and sources of data also used in the creation of algorithms used in AI potentially creates bias of data-gap; and lastly, the quality of data services and data infrastructures potentially impacts the standards and interoperability of data the AI algorithms are built on. A close look into all three AI accountability variables uncovers the unnoticeable effects of data biases on AI systems built for mobile health.

In light of the above, we can make inference from this study that while all three of the AI accountability variables have shown to have a statistically significant correlation with mobile health index, they in fact do not interfere in the relationship human freedom factors have with mobile health index. The absence of a mediation effect of these AI accountability variables invites the idea that both human freedom factors and accountability of AI developed in creating access to healthcare can independently impact an individual's use of digital or mobile health. It is also notable that the explainable disparity in mobile health by human freedom factors increases even more when the AI accountability variables are included in the model. Thus, our study confirms that health policy makers and developers will create much more impactful mobile health applications when consideration is given to both the level of accountability of the AI and also human freedom factors of the intended users. By enabling human freedom variables, we can improve access to healthcare services through mobile health; by ensuring AI algorithmic accountability, we can increase the quality of information available to users who seek access to healthcare services.

Past studies elucidate the idea that artificial intelligence models tend to have difficulty in representing human behavior. Yet they carry out tasks that can be carried out by trained professionals. For example, radiologists who are trained to screen X-rays are being replaced by AI engines that can detect cancer at rates that are more accurate than the human radiologists they replace. A predictive mathematical model is as seductive in its elegance as it is dangerous when powering an artificial intelligence application. Despite the exponential growth and precision of machine learning algorithms over the past thirty years, one thing remains the same: little is known about how the models arrive at their predictions. No matter how accurate the answers, the decision-making processes used by the machine learning algorithms remain elusive[15]. The decision making of the AI solutions have a need to provide accountability and transparency in their decision making. Lepri et al propose[20] the use of Open-source Algorithms to ensure fairness and transparency.

The impact of this research is in showing that there is a role for artificial intelligence in supporting digital inclusion and mobile health. Digital inclusion can be supported through artificial intelligence approaches especially in global health[6]. Han et al successfully demonstrate[22] the potential of using advanced Natural Language Processing (NLP) models like Bidirectional Encoder Representations from Trans-formers (BERT) in accurately identifying and classifying SDOH in clinical settings. Such methodological advancements offer tools for health professionals and researchers in aiding better understanding and addressing the social factors impacting patient health. Lepri et al concludes[20] that accountable algorithms in government and corporations' decision-making is fundamental in validating their utility towards public interest, while also rectifying the potential harms generated by the algorithms. Implementation of accountable algorithms and open-source algorithms have potential to support digital inclusion by public interests which can include public health.

Conclusion

Based on results from the regression models evaluating the mediation effects of each of the AI accountability variables, we can conclude that AI accountability does not mediate the effects of the relationship between human freedom and mobile health index. Rather, AI accountability (in terms of AI data-driven bias, AI data gap bias and lack of AI data standards) have significantly direct effects on mobile health. Essentially, with the inclusion of AI accountability variables in the regression model explaining mobile health, we found that AI accountability had the most contribution in each of these models; increasing the r-squared by approximately 40%.

The impact of this research is in showing that there is a role for artificial intelligence in supporting digital inclusion and mobile health. The decision making of the AI solutions have a need to provide accountability and transparency in their decision making. As the role of artificial intelligence is exacerbated with the digital technologies that are used, algorithmic accountability becomes a central issue. The analysis here confirms human freedoms are essential in enabling digital inclusion and mobile health. The role of accountability is important and human freedom determinants, except geo-economic factors, had a statistically significant relationship with mobile health index. The mediating variables – multidimensional poverty index and human development index were also significantly correlated with the mobile health index. There was a statistically significant correlation between the human freedom variables and AI data-driven bias. AI accountability also effects the ability of people to stay healthy using their mobile applications. Human freedom is important as people suffering from health issues facing poverty tend to suffer from algorithmic bias. The findings in the paper offer a means of conceptualizing algorithmic bias in a way that empowers the users of mobile health applications the freedom to train the applications to their personal preferences.

In summary, the implications from this research is that we can edge towards building mobile health applications capable of creating access to healthcare, while also ensuring it impacts the quality of available information on healthcare services being accessed, if we take into consideration the algorithmic accountability of the AI used in the development process of the application.

Acknowledgements

This research is supported by the Nebraska Research Initiative and Amazon Health Equity grants.

References

1. Sen, A. (2005). Human rights and capabilities. Journal of human development, 6(2), 151-166.
2. Zuboff, S. (2019, January). Surveillance capitalism and the challenge of collective action. In New labor forum (Vol. 28, No. 1, pp. 10-29). Sage CA: Los Angeles, CA: SAGE Publications.
3. Sieck, C.J., Sheon, A., Ancker, J.S., Castek, J., Callahan, B. and Siefer, A. 2021. "Digital inclusion as a social determinant of health," NPJ digital medicine, 4(1), 52. https://doi.org/10.1038/s41746-021-00413-8.
4. Rogers, C.C., Jang, S.S., Tidwell, W., Shaughnessy, S., Milburn, J., Hauck, F.R. and Valdez, R.S. (2023). "Designing mobile health to align with the social determinants of health," Frontiers in Digital Health 5, 1193920. https://doi.org/10.3389/fdgth.2023.1193920
5. Ye, J., Ma, Q.: The effects and patterns among mobile health, social determinants, and physical activity: a nationally representative cross-sectional study. In: AMIA Summits on Translational Science Proceedings, vol. 2021, pp. 653. (2021).
6. Qureshi, S. (2022). Creating cycles of prosperity with human digital development for intelligent global health. Information Technology for Development, 28(4), 649- 659.
7. Maghsoudi, T., Cascon-Pereira, R., & Beatriz Hernández Lara, A. (2020). The role of collaborative healthcare in improving social sustainability: A conceptual frame- work. Sustainability, 12(8), 3195.
8. Medina, F.-X. and Sole-Sedeno, J.M. (2023). "Social Sustainability, Social Capital, Health, and the Building of Cultural Capital around the Mediterranean Diet," Sustainability 15(5):4664. https://doi.org/10.3390/su15054664
9. Seth, R., Dhaliwal, B.K., Miller, E., Best, T., Sullivan, A., Thankachen, B., Shet, A.: Leveling the Research Playing Field: Decolonizing Global Health Research Through Web-Based Platforms. Journal of Medical Internet Research 25, e46897 (2023)
10. Masiero, S., Bailur, S.: Digital identity for development: The quest for justice and a research agenda. Information Technology for Development 27(1), 1-12 (2021). doi: 10.1080/02681102.2021.1859669
11. World Health Organization: Rio Political Declaration on Social Determinants of Health. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4910459/ (2011).
12. Norori, N., Hu, Q., Aellen, F. M., Faraci, F. D., & Tzovara, A. (2021). Addressing bias in big data and AI for health care: A call for open science. Patterns (New York, N.Y.), 2(10), 100347. https://doi.org/10.1016/j.patter.2021.100347
13. Ueda, D., Kakinuma, T., Fujita, S. et al. Fairness of artificial intelligence in healthcare: review and recommendations. Jpn J Radiol 42, 3–15 (2024). Doi: https://doi.org/10.1007/s11604-023-01474-3
14. Fletcher RR, Nakeshimana A and Olubeko O (2021) Addressing Fairness, Bias, and Appropriate Use of Artificial Intelligence and Machine Learning in Global Health. Front. Artif. Intell. 3:561802. doi: 10.3389/frai.2020.561802
15. Qureshi, S. (2023). Cycles of development in systems of survival with artificial intelligence: a formative research agenda. Information Technology for Development, 29(2-3), 171-183.
16. Mannuru, N. R., Shahriar, S., Teel, Z. A., Wang, T., Lund, B. D., Tijani, S., Pohboon, C. O., Agbaji, D., Alhassan, J., Galley, J., Kousari, R., Ogbadu-Oladapo, L., Saurav, S. K., Srivastava, A., Tummuru, S. P., Uppala, S., & Vaidya, P. 2023. "Artificial intelligence in developing countries: The impact of generative artificial intelligence (AI) technologies for development," Information Development, 0(0). https://doi.org/10.1177/02666669231200628
17. Larburu, N. Artetxe V., Escolar A., Lozano, and J. Kerexeta, "Artificial intelli- gence to prevent mobile heart failure patient's decompensation in real time: mon- itoringbased predictive model," Mobile Information Systems, vol. 2018, Article ID 1546210, 11 pages, 2018.
18. Wieringa M (2020) What to account for when accounting for algorithms: a systematic literature review on algorithmic accountability. In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency (FAT* '20). Association for Computing Machinery, New York, p. 1–18. https://doi.org/10.1145/3351095.3372833
19. Horneber, D., Laumer, S. Algorithmic Accountability. Bus Inf Syst Eng 65, 723–730 (2023). https://doi.org/10.1007/s12599-023-00817-8
20. Lepri, B., Oliver, N., Letouzé, E. Pentland, A. and Vinck, P. (2018). "Fair, Transparent, and Accountable Algorithmic Decision-making Processes," Philos. Technol. 31, 611–627. https://doi.org/10.1007/s13347-017-0279-x
21. Vandelanotte, C., Trost, S., Hodgetts, D., Imam, T., Rashid, M., To, Q. G. and Maher, C. 2023. "Increasing physical activity using an just-in-time adaptive digital assistant supported by machine learning: A novel approach for hyper-personalised mHealth interventions," Journal of Biomedical Informatics, 144, 104435.
22. Han, S., Zhang, R. F., Shi, L., Richie, R., Liu, H., Tseng, A., Quan, W., Ryan, N., Brent, D., and Tsui, F. R. 2022. "Classifying social determinants of health from unstructured electronic health records using deep learning-based natural language processing," Journal of biomedical informatics, 127, 103984. https://doi.org/10.1016/j.jbi.2021.103984
23. Sangers, T., Reeder, S., van der Vet, S., Jhingoer, S., Mooyaart, A., Siegel, D. M., & Wakkee, M. (2022). Validation of a market-approved artificial intelligence mo- bile health app for skin cancer screening: a prospective multicenter diagnostic ac- curacy study. Dermatology, 238(4), 649-656.
24. Xu, Z., Biswas, B., Li, L., & Amzal, B. (2023). AI/ML in Precision Medicine: A Look Beyond the Hype. Therapeutic Innovation & Regulatory Science, 1-6.
25. Xiaofeng Wang, Zhenshun Cheng, "Cross-Sectional Studies: Strengths, Weaknesses, and Recommendations", Chest, Volume 158, Issue 1, Supplement, 2020, Pages S65-S71, ISSN 0012-3692, https://doi.org/10.1016/j.chest.2020.03.012.