Can Generative Artificial Intelligence enable equitable access to Social Determinants of Health?

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Abstract

When people living in low resource environments struggle to access the resources they need live, they are faced with health inequities caused by lack of access to social determinants of health. This paper aims to understand the ways in which generative AI can enable equitable access to resources that are key to social determinants of health (such as dental health, mental health, domestic violence services, substance abuse services, among many others). In order to conduct the investigation, this research seeks to answer: 1) How can AI-powered mobile health services improve the state of social determinants of health? And 2) In what ways can a generative-AI mHealth chatbot enable access to healthcare? The questions are investigated, first through the testing of four hypotheses using data gathered from international agencies, and second through use cases of a chatbot powered through generative AI assisting access to location-based resources. This contribution uncovers key constructs and generative AI features that enable health equity.

Keywords: Generative AI, Social determinants of Health, AI in Healthcare, Mobile Health, Health Equity, Digital Inclusion.

1. Introduction

Generative Artificial Intelligence (GAI) has emerged as a prominent means of addressing the inequities among those who are trying to access basic resources needed to stay healthy. These resources are also known as Social Determinants of Health (SDOH) and are shown to effect health outcomes as explained in Qureshi et al (2024). This concept has gained application in diverse fields, including health, for its ability to create new content, which includes but not limited to text, by leveraging the power of AI and data to generate original and innovative outputs (Mannuru et.al., 2023).

Health inequities caused by discrepancies in social determinants of health, worsen health outcomes in areas such as cardiovascular disease and COVID-19 (Kiemde et al 2021). Sen (2001) notes that freedoms impact each other. For example, a person who is considered to be low on the socio-economic spectrum, knows that needing to go see a doctor could put them not only out of money, but out of a job and livelihood. (Qureshi, 2021; Qureshi & Xiong, 2021; Kiemde, Qureshi, & Clarke, 2021; Sen, 2001).

It is known that socio-economic standing effects health inequities and the abilities of people to stay healthy (Clarke et al., 2021; Qureshi & Xiong, 2021). Many doctors and researchers use patient-centered care in order to help people become healthy and stay healthy. Patient-centered care is important, because when people feel ownership over their own health then their health outcomes are improved (Clarke, 2015; Clarke, 2020). Patients make lifestyle choices relating to the food they eat and exercise they do.

At the same time, integrating Artificial Intelligence (AI) into mobile healthcare (mHealth) has transformed how medical services are delivered, majorly through improved diagnostic capabilities and personalized treatment plans. This evolution is an element of the broader shift towards HealthCare 4.0, which leverages massive data collection and analysis to improve healthcare outcomes, cost-efficiency, and patient engagement (Sharma et al., 2022). Generative Artificial Intelligence (AI) in the form of Large Language Models (LLMs) such as Chat GPT-4, BERT, Claude etc., are becoming powerful tools with significant applications in HealthCare.

As it has been used in multiple industries and sectors, generative AI is transformational, and its technology can be used to transform health care by

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processing and generating complex data (Mesko & Topol, 2023). LLM's has demonstrated in handling clinical documentation, streaming electronic health records and facilitating human-like patient communication (Xue et. al., 2023) thus improving patient visits. The capabilities of generative AI ranges from acting as assistance in diagnosing diseases, suggesting treatment plans, and managing health records efficiently, provision of insights to health care providers by processing vast amounts of medical data to enhance health care and operational efficiency.

In addressing this need for ICTs to help address inequities, this paper aims to understand the ways in which generative AI can enable equitable access to resources that are key to social determinants of health (such as dental health, mental health, domestic violence services, substance abuse services, among many others). In order to conduct the investigation, the research in this paper seeks to answer the following questions: 1) How can an AI-powered mobile health services improve the state of social determinants of health? 2) In what ways can generative-AI mHealth chatbot enable access to healthcare?

The first research question is investigated using data available from the World Bank Database and WHO metadata portal. Four measures are considered for the socio-determinant of health, which includes: Human Capital Index- Health component, Healthcare factors, Socio-economic factors, and Lifestyle factors. Using these constructs four hypotheses were tested using the Pearson Product Moment Correlation (PPMC).

The second research question is investigated through the use of the mhealthhelp.com application. This draws upon LLM models and APIs developed for use on mobile devices and desktop across all operating systems. The generative AI with location-based service and knowledge-base capabilities enable users living in low resource environments to access the resources they need to stay healthy and, in many cases, alive. In facilitating access to community health resources, the application attempts to address the inequities in healthcare outcomes for people living in low resource environments.

The following sections offer a theoretical background of digital inclusion, social determinants of health and Generative AI in Health Care. The methodology explains how the two research two questions are investigated, first through the testing of four hypotheses using data gathered from international agencies, and second through use cases to understand how a chatbot powered through generative AI can assist users in low resource environments access the resources they need to stay healthy and alive.

2. Theoretical Background

2.1 Digital Inclusion for Health Equity

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 (Sieck et al 2023).

According to the UNDP Human Development index, in order to live a free and healthy life, health equity is needed. Health equity is a form of distributive data justice and a form of social opportunities (Sen, 2001; Martin & Taylor 2021). Distributive data justice is when everyone has the access to the same resources regardless of their social circumstances (Martin & Taylor 2021). Braveman and Gruskin state that "health disparity is inequitable if it is systematically associated with social disadvantage in a way that puts an already disadvantaged social group at further disadvantage" (Braveman & Gruskin, 2003).

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. (2023) and Jiancheng Ye & Qianheng Ma (2021) illustrate this interaction vividly. Rogers et al. 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, Jiancheng Ye and Qianheng Ma's (2021) study 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.

Furthermore, the broader implications of digital technologies in health are explored in studies by Seth et al. (2023), Medina & Sole-Sedeno (2023), and Sieck et al (2023). Seth et al.'s (2023) discussion 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 (2023) highlight 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 (2021) delve 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.

Finally, Sieck et al. (2023) and Martin & Taylor (2021) focus on digital inclusion in healthcare and the implications of digital identification systems for vulnerable populations, respectively. Sieck et al. highlight the digital divide's impact on health, advocating for sup- port in digital literacy and connectivity, while Martin & Taylor (2023) discuss case studies from Uganda and Bangladesh, showing the dual potential of digital systems in both enabling and impeding access to essential services.

Together, these studies underscore the complexity of achieving digital inclusion and integrating mHealth with SDOH. 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.

2.2 Social Determinants of Health

World Health Organization (WHO) defines Social Determinants of Health (SDOH) as the conditions in which humans are born, grow, work, live, age, and the forces and systems that shape the conditions of daily life" (WHO, 2011). Historically, medical community considered non-medical factors of SDOH such as living conditions, age, working conditions, and place of birth as secondary influences on human health. Most of research work done on healthcare was concentrated on patient-centered care and empowerment (James, 2013). But latest research on human health has increasingly shown that these social determinants—including living conditions, access to resources such as education, food, clean and air, and economic stability—are directly associated with onset of many diseases and hold significance on human health. This section explores recent studies on SDOH and how technology can be leveraged to improve human health. In particular, it considers the following studies to illustrate, how some social determinants can be detrimental to individual and community health.

A research paper by Clarke and other talks on patient-empowerment suggests that patients who actively have access to their own medical information, can overcome health issues and have positive outcomes for individual health when compared with patients with less access to medical information (Clarke et al., 2020; Clarke et al., 2021). However, everyday stressors act as roadblocks in some patient lives and stop them from actively engaging with digital health tools, which are increasingly facilitated by mobile health(mHealth) applications. Another study on individual health points out that the community health is dependent on individual health and any effect on individual health will have impact on the community health which in turn affects local economy, lack of proper economic means can impact community health thus creating a cyclical relationship (Kahn et al., 2010).

At the national level in the USA, Kiemde et al. (2022) found that Information and Communications Technologies (ICT) can help people access essential resources, alleviating conditions related to poverty, lack of insurance, and inadequate education, and are particularly beneficial for those in rural areas. Kiemde and Qureshi (2022) study discovers the social determinants that are related to human development and how access to mHealth is related to SDOH and the Human Development Index (HDI). Access to mHealth correlates with SDOH and the Human Development Index (HDI) globally, suggesting that mHealth applications can address inequalities and foster human development across the world.

Several factors such as household income are contributing to the common mental disorders and hold significant influence on the educational achievement, material hardship, and unemployment (Fryers et al., 2005). Cockerham et al. (2017) points out that unhealthy behaviors such as smoking, alcoholism, and substance abuse are most common in individuals from lower socio-economic status and disadvantaged neighborhoods. These unhealthy behaviors are more likely to be seen in people from lower socio-economic background compared to those from higher socio-economic backgrounds. These behaviors are linked to a range of health issues, including cancers, diabetes, pulmonary diseases, pneumonia, and mental health challenges.

Recent research over the last decade continues to explore the complex relationships between various social determinants and health outcomes. This study categorizes SDOH into their associated health resource categories. Lemstra et al. (2008) found that young individuals aged between 10 to 15 from lower socio-economic backgrounds are 2.5 times more likely to suffer from depression and anxiety compared to those from higher socio-economic statuses. These studies underscore how SDOH such as household income, unemployment, and limited educational opportunities can exacerbate mental disorders and increase the prevalence of depression and anxiety among young adults.

2.3. Generative AI in Health Care

Generative Artificial Intelligence (AI) in the form of Large Language Models (LLMs) such as Chat GPT-4, BERT, Claude etc., are becoming powerful tools with significant applications in HealthCare. Generative AI is poised to transform multiple industries including health care by processing and generating complex data (Mesko & Topol, 2023). LLM's has demonstrated in handling clinical documentation, streaming electronic health records and facilitating human-like patient communication (Xue et al, 2023) thus improving patient visits. Generative AI is capable of assisting in diagnosing diseases, suggesting treatment plans, and managing health records efficiently. Generative AI can provide insights to health care providers by processing vast amounts of medical data, which can enhance health care and operational efficiency.

However, the integration of generative AI in healthcare does not come without challenges. Transparency and accountability are the major concerns due to the "black box" nature of AI systems which are critical in medical settings as the Generative AI decisions significantly impact patient lives (Zhang et al, 2023). Ethical considerations, such as privacy, consent, and the potential amplification of existing biases, must be meticulously managed (Zhang et al., 2023).

Zhang insists that the regulatory frameworks need to evolve to keep pace with technological advancements to ensure that generative AI tools are safe, reliable, and fair (Zhang et al., 2023). Though Generative AI has some changes, the potential benefits of generative AI in healthcare are huge and can lead to earlier and more accurate diagnoses, improved health outcomes, all while potentially reducing costs. Establishing robust regulations will be crucial in maintaining trust in AI-assisted healthcare services and ensuring that these technologies enhance rather than compromise patient care to fully realize these benefits (Zhang et al., 2023). Ensuring they complement the skills of medical professionals and adhere to strict standards of safety and efficacy. As these technologies evolve, continuous collaboration between AI developers, healthcare professionals, and regulatory bodies will be crucial to address the ethical implications and integrate these tools responsibly into healthcare practice.

2.4. Artificial Intelligence in Mobile Health

The rising number of smartphone users is fueling an increased reliance on mobile applications, which in turn is promoting a greater use of AI based mobile applications. The integration of Artificial Intelligence (AI) into mobile healthcare (mHealth) is transforming how medical services are delivered, particularly through improved diagnostic capabilities and personalized treatment plans. This evolution is part of a broader shift towards HealthCare 4.0, which leverages massive data collection and analysis to improve healthcare outcomes, cost-efficiency, and patient engagement (Sharma et al., 2022). Through the use of technologies such as wearable devices and mobile applications powered by AI algorithms, such as Convolutional Neural Networks (CNNs) and LLMs, mHealth is transforming the way healthcare is accessed and delivered. Mobile devices equipped with AI capabilities enable real-time health monitoring and data analysis, which facilitates instantaneous medical decision-making and preventive healthcare management.

These AI-driven systems harness the power of data analysis and machine learning algorithms to process vast amounts of health data collected via mobile devices, enabling early diagnosis and intervention in various medical conditions. For instance, through continuous monitoring of vital signs and other health indicators, AI algorithms can identify patterns and anomalies that may indicate the onset of a condition, thereby alerting healthcare providers and patients at the earliest stages when human interventions are most effective (Khan & Alotaibi, 2020).

The use of AI-driven algorithms in mobile applications allows for the continuous collection and analysis of health data, providing critical insights into patient health trends and potential health risks. In practical terms, particularly in the realm of echocardiography and cardiovascular health. Advances in mobile computing and handheld imaging technologies have empowered healthcare professionals with tools that were unimaginable just a few years ago. AI's role in this revolution is pivotal, as it provides sophisticated data analysis capabilities that are essential for interpreting the vast amounts of health data generated by these technologies (Seetharam et al., 2019). This integration not only enhances diagnostic precision but also democratizes health monitoring and intervention, making it accessible even in resource-limited settings (Seetharam et al., 2019).

Moreover, AI augments the human touch into healthcare by supporting more personalized patient interactions and care plans. Mobile apps equipped with AI can analyze patient data in real time, offering tailored health recommendations and adjustments to treatment plans based on individual patient responses. This tailored approach not only improves patient outcomes but also enhances patient engagement and trust in healthcare by providing them with insights into their health status and progress. Additionally, AI-powered mobile health applications can reduce the burden on healthcare systems by automating routine tasks, such as data entry and analysis, thus allowing healthcare professionals to focus more on patient care rather than administrative tasks. The integration of AI into mHealth is not just a technological advancement but a significant step towards making healthcare more patient-centric, accessible, and efficient (Khan & Alotaibi, 2020).

In answering the research question the following hypothesis were tested:

H1: AI index has a significant effect on human capital index (HCI)

H2: AI index significantly affects healthcare factors

H3: AI index significantly affects socio-economic factors

H4: AI index has a significant impact on lifestyle factors.

3. Methodology

Since our research seeks to answer two distinct questions, two methodologies are triangulated to offer evidence in providing answers to these questions. The first research question "How can AI-powered mobile health services improve the state of social determinants of health?" is investigated using data available from the World Bank Database and WHO metadata portal. From these databases, variables related to healthcare factors, socio-economic factors, lifestyle factors and human capital index (health component) were selected to be used for our analysis.

Using the appropriate variables, four composite measures were derived. These composite measures are considered as the socio-determinant of health (SDOH) used in this article, which includes: Human Capital Index- Health component, Healthcare factors, Socio-economic factors, and Lifestyle factors. The following table 1 illustrates the variables that are constituents of each of the measures:

Constructs	Variables	Definition
AI Index (Statistical Performance Indicator)	Data use Data services Data products Data sources Data infrastructure	The Statistical Performance Indicator is a measure of how the statistics must "meet the test of practical utility", serving "the Government, the economy and the public with data about the economic, demographic, social and environmental situation." The statistics are indirectly functions of how AI is harnessed to improve quality of data in each of the countries. The SPI is calculated by taking the simple average of its 5 pillars (data use, data services, data products, data sources, data infrastructure), and by formula: $SPI_{index} = \sum_{p=1}^{N_p} \frac{SPI_{pil}}{N_{pil}}$ ... where SPI_{pil} is the computed score for each pillar, derived by the formula: $SPI_{pil} = \sum_{d=1}^{N_d} \frac{\omega_{pd} \times SPI_{dim}}{N_d}$ …where ω_{pd} is the weight for dimension 'd' in a given pillar 'p'.
HCI		The Human Capital Index (HCI) measures the human capital that a child born today can expect to attain by age 18, given the risks to poor health and poor education that prevail in the country where she lives. Proportion of women with child delivery at a healthcare facility (WHO, 2023). HCI is constructed by multiplying the contributions of survival, school, and health to relative productivity, as follows (WHO, 2023): HCI = Survival × School × Health …where $\text{Survival} = \frac{1 - '\text{Under}-5\text{ mortality rate}'}{1}$ $\text{School} = e^{0.08(\text{expected years of school} \times \frac{\text{harmonized test score}}{625} - 14)}$ $\text{Health} = e^{\frac{(0.65 \times (\text{adult survival rate}-1)) + (0.35 \times (\text{not stunted rate}-1))}{2}}$
Healthcare factors	Infant mortality rate	Mortality rate between birth and 11 months per 1000 live births (WHO, 2023).
	Neonatal mortality rate	Mortality rate between birth and first 28 days per 1000 live births (WHO, 2023).
	Maternal mortality rate	Maternal mortality ratio (modeled estimate, per 100,000 live births) (WHO, 2023)
	Skilled birth attendant	Births attended by skilled health staff (% of total) (WHO, 2023)
	UHC service coverage index	A measure of the coverage of essential health services (WHO, 2023)
	Health expenditure	Health Expenditure, % of GDP (WHO, 2023)
Socio-economic factors	Literacy rate (Adult)	Proportion of adults, 15+ years, who are literate.
	Unemployment rate	Percentage of the total labor force who are unemployed (World Bank, 2023).

	Life Expectancy	Life Expectancy at Birth (World Bank, 2023)
	Electricity access	% of population with access to electricity (World Bank, 2023)
	ICT Export	ICT Exports, % of service exports (BoP) (World Bank, 2023)
Lifestyle factors	Alcohol consumption	Alcohol Consumption per capita (World Bank, 2023)
	Tobacco use	Prevalence of current tobacco use (% of adult) (World Bank, 2023)
	HIV Incidence	Incidence of HIV in the population (World Bank, 2023)

Table 1: Factors, Indexes and Variable description

With these constructs in place, four hypotheses were tested using the Pearson Product Moment Correlation (PPMC) and linear regression. The hypothesized relationship between the selected SDOH and AI Index is based upon the theoretical frameworks used in previous studies (Qureshi & Oladokun, 2024; Qureshi S., Oladokun B. & Nadendla K., 2024), where they conceptualized the relationship between human freedoms and mobile health, mediated by AI accountability. Using a much simpler but similar approach, in this study, we are looking at the two-directional relationship between SDOH and AI index; i.e. effect of SDOH on AI index and vice versa.

The second research question: Can generative-AI enable access to healthcare? is investigated by presenting actual use cases of the demo version of the mHealth Application, designed to act as an assistant to users who need information on healthcare services available to them. The application includes a chatbot and conversational agent capable of providing AI assistance to human (users). The bot and agents are built on Anthropic Claude that uses a 'Human' and 'Assistant' format, where the user types in their query using any grammatical construct that makes sense to them. The 'Assistant' – which is built on the Anthropic-Claude Generative AI queries the knowledge base and provides a response with information that is as accurate as possible.

The architecture of the agent revolves around having a user query which is passed onto the LangChain framework used for modifying the queries, interacting with the GooglePlaces API and retrieving response to queries from the Anthropic- Claude foundational model. Importantly, the user query modification is done with Retrieval Augmented Generation (RAG) in the LangChain framework. The mHealth agent passes the query to either the GooglePlaces API or the Amazon Titan Embeddings model, depending on the type of query. Location based queries are passed to the LangChain framework interacting with the GooglePlaces API, while domain-specific queries are passed to the Amazon Titan Embeddings trained on information extracted from peer-reviewed journal. While the results from GooglePlaces API call is passed directly to the agent as answers to the user query, the results from the Amazon Titan Embeddings are firstly passed to the Anthropic-Claude foundational model of the LangChain framework, where the responses are refined to ensure the user query is being properly answered and out-of-context responses are not given to the users. Overall, the application retrieves data to process its responses from two sources: First, the GooglePlaces API – which is essentially the API that provides access to data on Google maps. Second, our mHealth database, which is a compilation of peer-reviewed journals in the specific domain of mobile health for healthcare access, social determinants of health and healthcare access. The application can be accessed through: www.mealthhelp.com. The development and design science behind this mHealth application is detailed in our previous study (Qureshi S., Oladokun B. & Nadendla K., 2024).

4. Results and Analysis

In order to investigate the first research question Can AI-powered mobile health services improve the state of social determinants of health? the following hypotheses were tested:

H1: AI index has a significant effect on human capital index (HCI)
H2: AI index significantly affects healthcare factors
H3: AI index significantly affects socio-economic factors
H4: AI index has a significant impact on lifestyle factors.

Using the Pearson Product Moment Correlation (PPMC), we found that all four socio-determinants of health were significantly correlated with AI index. Human Capital Index (HCI) had the strongest correlation with a correlation coefficient of 0.8; indicating a very strong and positive relationship with AI index. Healthcare factor had a fairly strong correlation with AI index ($r = 0.63$). The relationship between socio-economic factors and AI index was positive and significant but not particularly strong ($r = 0.45$). Lastly, a negative but weak relationship was observed between lifestyle factors and AI index ($r = -0.43$).

Regressing AI index on the four socio-determinants considered in this study, our result is presented below. From the result, we found that Human Capital Index (HCI) and lifestyle factors had a statistically significant effect on AI index, with the effect of other factors being held constant. No significant effect on AI index was observed with healthcare factors and socio-economic factors as other socio-determinants of health are being held constant. Importantly, the result showed that a unit increase in the HCI of a country adds about 0.79 to the AI index of that country; conversely, a unit increase in the lifestyle factors of a given country reduces the AI index of such country by 0.08. The model adequacy, measured by its r-squared, confirmed that all four socio-determinants of health were able to explain up to 65.8% of the variation in AI index.

Hence, the result from this analysis suggests that HCI and lifestyle factors of a country have a huge role to play in explaining its AI characteristics.

	AI Index on Socio-determinants of Health (R^2=0.6580; p= <0.001)	
	Β	p-value
Intercept	31.68	< 0.001
HCI- health component	0.70	< 0.001
Healthcare factors	0.06	0.427
Socio-economic factors	0.01	0.930
Lifestyle factors	−0.08	0.022

Table 2. Regression Analysis: AI Index against Socio-determinants of Health

The table 3 below shows the result of each socio-determinant of health regressed on AI index. In this analysis, we found that AI index had a statistically significant effect on each of the four socio-determinants of health. With Human Capital Index, we found out that a unit increase in the AI index increases the HCI by 0.78; with an r-squared of 0.6434, indicating that AI index potentially accounted for up to 64% of the variation in HCI. For other socio-determinants of health, we found that a unit increase AI index potentially increases the healthcare factors by 0.79, improves socio-economic factors by 0.55, and lead to a reduction in lifestyle factors by 0.6.

Consequently, from these results, we can infer that the AI characteristic of a country impacts HCI much more than it does to the other 3 socio-determinants of health used in this study.

HCI on AI Index ($R^2 = 0.6434;\ p = < 0.001$)		
	β	p-value
Intercept	−0.781	0.828
AI Index	0.783	< 0.001
Healthcare Factors on AI Index ($R^2 = 0.399;\ p = < 0.001$)		
	β	p-value
Intercept	17.34	0.002
AI Index	0.79	< 0.001
Socio-economic Factors on AI Index ($R^2 = 0.2064;\ p = < 0.001$)		
	β	p-value
Intercept	20.24	< 0.001
AI Index	0.55	< 0.001
Lifestyle Factors on AI Index ($R^2 = 0.1868;\ p = < 0.001$)		
	β	p-value
Intercept	77.34	< 0.001
AI Index	−0.60	< 0.001

Table 3. Regression Analysis: Socio-determinants of Health on AI index

The above analysis suggests that that AI index correlates significantly with the Human Capital index, Healthcare factors, socio-economic factors and lifestyle factors.

5. Digital Inclusion through Generative AI

In order to investigate the second research question Can generative-AI enable access to healthcare? This section offers findings from three use cases of the mHealth Chatbot and Conversational Agent. These use cases were actual responses obtained from the demo version of our trained bot and agents, designed to take-in a human query and provide responses as AI assistant. The mhealthhelp.com application offers users the use of location-based service. This allows the mhealthhelp.com application to carry-out its functions including searching, finding, navigating and retrieving vital information of community resources where health services can be consulted.

Conversely, the use of a knowledge-base allows for querying the generative AI model to provide information on topics within the scope of interest (social determinants of health, mobile health, digital inclusion, etc.). By appropriately combining the technological power of location-based services, knowledge-base, and generative AI, the application being enables people living in low resource environments to access the level of social determinants of health they need located in their communities so they may stay healthy or in some cases alive.

In the first use case (Figure 1), the chatbot was queried for ‘Dental Services within the Omaha metro’. Following this input, the AI-assistant (chatbot) responded with a minimum of 20 distinct service centers in the City of Omaha, where dental services could be obtained. Providing pertinent details in terms of address to the service center and phone numbers, allowing users to multiple choice of providers for dental services. This feature relies on data available on Google maps, through the AI-assistant interaction with GooglePlaces API. This is illustrated below in figure 2:

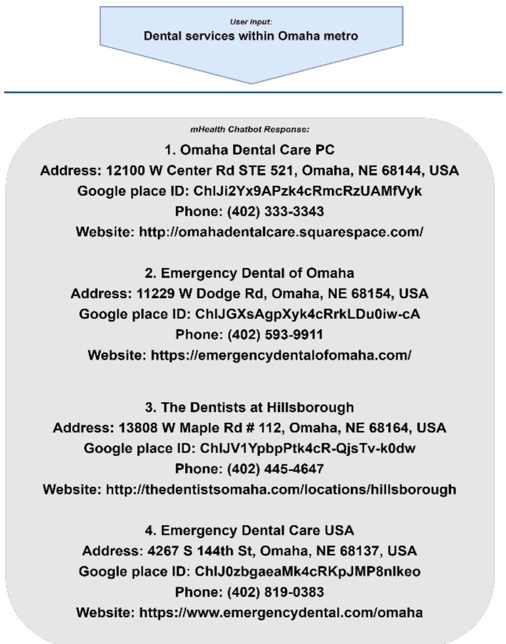

Figure 2. Use Case of mHealth Chatbot for location-based query

As a further step, we queried the chatbot to provide details on what specific services can be obtained from a particular dental service provider on the list. With the aid of relevant web-crawlers, the chatbot adequately interacted with the provider's website to pull a request on services offered by that provider. In the second use case presented below, the AI-assistant (chatbot) responded accurately with the services the chosen provider offered (as explicitly stated on the provider's website). While this feature relies solely on a provider having a website and the information provided on their website, we confirmed that our AI-assistant is capable of interacting with external websites to provide details to users who may have more queries regarding what services are available to them from any of the providers on the location-based query list. This is illustrated in figure 3 below:

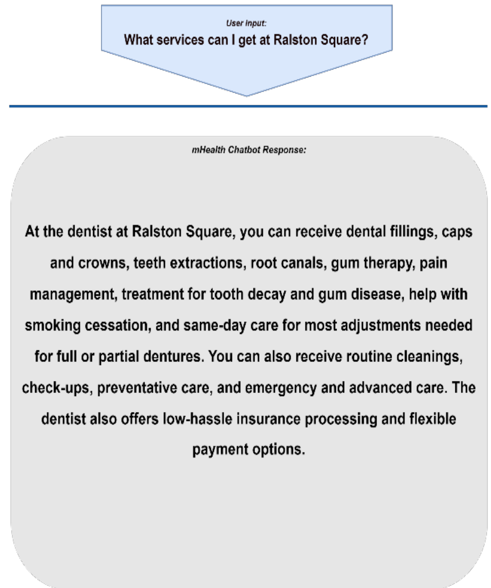

Figure 3: Use Case of mHealth Chatbot for getting more details following a location-based query

Use case 3 (Figure 4) illustrates how the AI-assistant aided knowledge on questions that are within the domain of mobile health and socio-determinant of health. The human input in this case was 'What are the benefits of mobile health?'. In this case, we found out that the AI-assistant was capable of providing answers to questions in this field, with the aid of the large language model trained with abundant information from peer-reviewed documents within the domain of mobile health and socio-determinant of health.

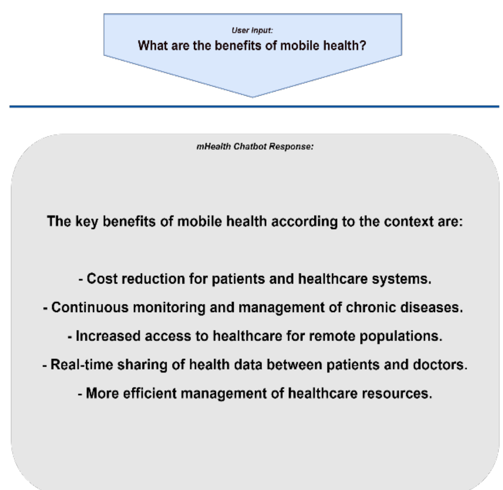

Figure 4: Use Case of mHealth Conversational Agent for answering domain-specific questions

6. Discussion

The impact of this research is in showing that there is a role for artificial intelligence in supporting digital inclusion and mobile health (Qureshi & Oladokun 2024). In alignment with previous research this research found that use of chatbot to enhance access to healthcare services at community level has been established. One of these examples is an application known as *Layla*- a community-based application developed to act as a trusted source of information within the domain of contraception and sexual health (Bonnevie E. et. al., 2020). In their study, Wilson et. al. (2022) reported that up to 66% of the studies reviewed on Chatbot development confirmed the use of custom-developed chatbot on web platforms, essentially chatbot integrated with a web application. While some chatbots can be developed on existing social media, via SMS, or Google Assistant platforms; integrating the chatbot into a web application remains the most efficient way to make it accessible to its users.

The use of generative AI in IT development for mobile healthcare has been on the rise, as seen in several literatures reviewed for this paper. With specific instances ranging from skin cancer assessment (Sangers et.al., 2022) to precision medicine (Xu et.al., 2023). In addition to those, our research found out that generative-AI does not only apply to clinic-based medicine but also in providing seamless access to healthcare as a community resource. This is achieved by harnessing the power of the Anthropic-Claude foundational model within the Langchain framework in creating the mHealth Chatbot and Conversational agent for users who desire specific resources in any community they may find themselves. In this vein, the study further confirms applicability of generative AI in healthcare access generally, while also closing the gap between the proffering a solution to healthcare access problem and evaluation of the given solution to ensure algorithmic accountability, AI fairness and AI biasedness.

Essentially, the result of this research – confirming usability of generative AI in healthcare access – is a foundational step to quantifying and assessing how AI can be developed to be participant-centered, fair, biased-free and held accountable, on the basis of the responses and feedback from its users. For the case of the mHealth Chatbot and Conversational agent, a successful design science of this application brings us towards the understanding of the algorithmic biases that may or may not exist in our participant-centered solution – which can be achieved easily in our future research, since we are developers of the application and have complete access to the algorithms making decisions for users of our application (Qureshi et al 2024).

7. Summary, Conclusion, Limitations and Future Research

This research has investigated the ways in which generative AI can enable equitable access to resources that are key to social determinants of health (such as dental health, mental health, domestic violence services, substance abuse services, among many others); and offered a view of how a generative AI powered chatbot can assist users in accessing the resources they need to stay healthy. The following research questions have been investigated: 1) How can AI-powered mobile health services improve the state of social determinants of health? 2) In what ways can generative-AI mHealth chatbot enable access to healthcare? These questions are investigated, first through the testing of four hypotheses using data gathered from international agencies.

The findings suggest that there are significant correlations between the AI index and the Human Capital index, Healthcare factors, socio-economic factors and lifestyle factors. The second question was investigated through use cases of a chatbot powered through generative AI assisting access to location-based resources. This contribution uncovers the generative AI features that enable health equity.

By so doing the research does not only develop a practical solution to a pertinent problem but it also adds to the body of knowledge within the scope of information technology. In this vein, this research is beneficial to the common user in the society through their use of the mHealth App, while also creating knowledge for researchers in the field of AI and health on how to successfully create chatbot for healthcare access.

The limitations of this study lie in that that beyond the testing of hypotheses, this study cannot be generalized across different contexts. As can be seen from the use cases, the mHealth chatbot application still needs to be tested across multiple contexts. A design science approach was used to develop the application, collecting data through it remains an ongoing process (Qureshi et al 2024). While the hypothesized relationships were tested, further consideration needs to be given to queries that are pertinent to the benefits of the users. In addition, while we confirmed the chatbot works in any location where GoogleMaps API is functional, the actual testing of location-based feature of the application by the developers was done within the United States area. Future research can be expanded to include real user testing of the application, in different countries across the globe.

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