Increasing Adoptive Capacities of Innovative Health Technologies in the Global Health Care System

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Abstract

AI usage in healthcare is still in its infancy and has not yet reached its potential to make the global healthcare system more equitable and safe. There is a substantial gap between AI promises and its actual delivery in healthcare settings. AI is a social-technical system and AI technology alone cannot solve our health equity issue. This is the research question: What social, political, and economic elements in the global health system must be addressed such that the capacities of AI can be optimized? The paper employs qualitative research to seek expert opinions, investigate the success cases of implementing particular AI devices in Hong Kong and Singapore, and integrate the lessons learned from the adoption of 87 AI-technology initiatives in a large Canadian hospital. The author recommends how the supply side increases their trustworthiness and the demand side grows trust. The supply side includes technology providers, legal, policy, and professional organizations, venture capitalists, and academic research institutions need to provide responsible AI and govern AI for long-term benefits. Increasing trust from healthcare organizations, including the presence of champions, organization alignments, funding mechanisms, new professional identities, patients' digital and health literacy capabilities, and supportive organization culture, is recommended. The same AI devices should be interoperable among the healthcare systems in and outside their countries. Standardized data quality assessment, benchmarking datasets, funding mechanisms, and agreement on model and clinical performance measures need to be used to facilitate comparison across products and settings. Investment in supporting digital infrastructure in low and middle-income countries is essential for the effective operation of AI devices. Various stakeholders must continuously demystify AI and participate in the collaborative work with those who have less power in the system.

Key words: *Data quality assessment; socio-technical system; champions; funding mechanism; organization alignments*

Anotacija

Dirbtinio intelekto naudojimas sveikatos priežiūros srityje dar tik pradeda veikti ir dar nepasiekė savo galimybių ribos, kad pasaulinė sveikatos priežiūros sistema būtų teisingesnė ir saugesnė. Egzistuoja didelis atotrūkis tarp DI pažadų ir realaus jo įgyvendinimo sveikatos priežiūros įstaigose. DI yra socialinė-techninė sistema ir viena pati DI technologija negali išspręsti mūsų sveikatos problemų. Šio tyrimo klausimas: į kokius socialinius, politinius ir ekonominius pasaulinės sveikatos sistemos elementus reikia atsižvelgti, kad dirbtinio intelekto pajėgumai būtų optimizuoti? Straipsnyje naudojami kokybiniai tyrimai, siekiant gauti ekspertų nuomones, ištirti tam tikrų DI įrenginių diegimo Honkonge ir Singapūre sėkmės atvejus ir integruoti nuo 1987 DI technologijų iniciatyvų didelėje Kanados ligoninėje priimtas ir įgytas pamokas. Autorius rekomenduoja, kaip pasiūlos pusė padidina jų patikimumą, o paklausa – pasitikėjimą. Pasiūla apima technologijų tiekėjus, teisines, politikos ir profesines organizacijas, rizikos kapitalo investuotojus ir akademines tyrimų institucijas, kurios turi teikti atsakingą dirbtinį intelektą ir valdyti AI, kad gautų ilgalaikę naudą. Rekomenduojama didinti sveikatos priežiūros organizacijų pasitikėjimą, įskaitant lyderių buvimą, organizacijų derinimą, finansavimo mechanizmus, naujas profesines tapatybes, pacientų skaitmeninio ir sveikatos raštingumo gebėjimus ir palankią organizacijos kultūrą. Tie patys dirbtinio intelekto įrenginiai turėtų būti suderinami tarp sveikatos priežiūros sistemų savo šalyse ir už jų ribų. Norint palengvinti produktų ir parametrų palyginimą, reikia naudoti standartizuotą duomenų kokybės vertinimą, lyginamuosius duomenų rinkinius, finansavimo mechanizmus ir susitarimą dėl modelio ir klinikinio efektyvumo priemonių. Investicijos į skaitmeninės infrastruktūros palaikymą mažas ir vidutines pajamas gaunančiose šalyse yra būtinos, kad dirbtinio intelekto įrenginiai veiktų efektyviai. Įvairios suinteresuotosios šalys turi nuolat demistifikuoti DI ir dalyvauti bendradarbiaujant su tais, kurie turi mažiau galios sistemoje.

Reikšminiai žodžiai: *duomenų kokybės vertinimas; socialinė-techninė sistema; čempionai; finansavimo mechanizmas; organizacijos derinimas.*

Introduction

Artificial intelligence (AI) is emerging as a key force in transforming the current healthcare system, enabling people from all backgrounds to access better quality health care (Bajwa et al., 2021; Maleki Varnosfaderani & Frorouzanfar, 2024; Sutton, 2024; WHO, 2021). However, the successful translation of machine learning products into clinical care remains rare (Sendak et al.,

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2020). As Greenhalgh et al. (2017) state, “AI in healthcare is still in its infancy” (Greenhalgh et al., 2017). A significant gap exists between AI’s promises and its deliveries in healthcare settings. The integration of AI within healthcare organizations and systems remains limited (Alami et al., 2024). AI technical solutions alone cannot solve our health equity issue! “AI systems are fundamentally socio-technical, including the social context in which they are developed, used and acted up, with its variety of stakeholders, institutions, cultures, norms and spaces” (Dignum, 2021). Power and values of different stakeholders determine how AI system can be integrated in the particular healthcare system. The success of implementing AI in a local context must fulfill the interests of politicians, patients, physicians, insurers, and other stakeholders.

In this paper, the author builds on an extensive literature review of AI in the global healthcare system, successful cases of implementing imaging AI devices in Hong Kong and Singapore, insights of integrating 87 AI technology-based initiatives in a large Canadia hospital by using Non-adoption, Abandonment, Scale-up, Spread, Sustainability (NASS) framework, and personal interviews with more than 50 experts including AI-start ups, physicians, venture capitalists, entrepreneurs, scientists, and health care administrators in Hong Kong, Dubai (UAE), China, and Germany. The main contributions are to recommend responsible AI from the supply side and trust from health care organizations. This article proceeds with three sections. The first section describes the methodology. The second section describes the successful cases of implementing imaging AI devices in Hong Kong and Singapore, and also unsuccessful cases in the U.S., Canada, and other developing countries. The third section recommends responsible AI from the supply side. The fourth section recommends trust from the demand side. The fifth section proposes some changes.

Methodology

Positionality – The author was born in Hong Kong and is an Chinese American woman. She has worked for her family business in the medical devices industry for recent years and aims to bring more affordable and effective AI medical devices to Hong Kong hospitals.

Methods –The author builds on an extensive literature review of AI in the global healthcare system and personal indepth interviews with suppliers and users of AI devices. During 2023-2024, the author interviewed more than 50 AI-start ups, and global manufacturers and investors at international medical exhibitions in Hong Kong, Dubai (UAE), Germany, China, and the Philippines. The author also attended more than 20 relevant AI seminars in Hong Kong and listened to the opinions of users including health administrators, doctors, nurses, and politicians. She also listened the success stories of implement imaging AI medical devices in Hong Kong and Singapore and had verified the information by talking to speakers and reviewing published information. She also used the Greenhalgh et al., (2017)’s NASS framework to address adoption but also non-adoption and abandonment of technologies and the challenges associated with moving from a local demonstration project to a fully mainstream project (i.e., scale-up), transferrable to new settings (spread), and maintaining long-term usage through adaptation. This framework has been used by other researchers in their inquiries about the application of AI in healthcare systems in Canada (Alami et al., 2024). The framework includes seven elements: complex conditions of illness, technology, value propositions from different stakeholders, the adopter system, an organization’s capacity to innovate and implement changes, the wider system, and scope of adaptation over time and organizational resilience. In this complex system, uncertainties and changing goals and values persist. Thus, the successful cases are drawn from personal interviews, listening to champions in public research forums, and secondary data. The unsuccessful cases in the U.S. and Canada are mainly gotten from literature review. The author synthesizes her learning from the successful and unsuccessful cases of integrating AI in healthcare systems, and different stakeholders’ needs and perspectives, and then recommends responsible AI from the supply side and trust AI from the demand side (i.e., healthcare organizations).

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Successful and Unsuccessful Cases

The trustworthiness of AI can be enhanced when a dedicated champion within a department has sufficient financial support and stakeholder involvement. The champion can decide whether to adopt or develop their own devices in the local context with proven clinical data in the local context. The fully support of politicians, patients, and physicians is essential for the successful implementation of mature AI-medical devices in public hospitals.

For example, the widespread adoption of AI in Hong Kong's public radiology department relies on a champion who can experiment and validate AI claims with stakeholders and financial backing within the existing data privacy regulations. The champion, an enthusiastic radiologist, integrates mature AI technology into the existing workflow, demonstrating to stakeholders that AI will not replace radiologists but will support them. AI is proven to reduce these radiologists' workloads, allowing them to focus on immediate patient interventions, leading to faster and more accurate treatments. With support from a charitable foundation, a successful pilot scheme in one hospital can be quickly adopted by others. The champion told the author he chose this mature technology AI applications in X-ray imaging as it has been adopted twenty years ago and can be easily proved to reduce the workload of radiologists. He initially used the American one in his three years' demonstration and kept on educating key stakeholders about its effectiveness. Later, a well-known charitable foundation determined to support an Australian company. Then his hospital also used the Australian one as the standards in the tender process. In Hong Kong, 42 hospitals are run by Hospital Authority. As his public hospital has earned significant recognition by adopting the AI in the radiologist department. Other 41 hospitals don't want to be excluded and want to adopt the same model provided by the Australian company. Quickly more doctors initiate to be champions in their own specialist departments. They modify existing mature AI medical devices and develop their own devices to widen the scope of imaging in different areas such as hip, breast, and eye radiologist with the support of government funding. Thus, AI-imaging medical devices are widely accepted and integrated in the existing public hospital system. Later, private hospitals also want to be better than public hospitals and also adopt similar AI-imaging medical devices. The success of implementing imaging AI devices also increases the image of Hong Kong as an international innovative health hub.

Another example is the successful integration of AI devices detecting referable diabetic retinopathy (DR), Singapore Eye Lesions Analyzer (SELENA), in Singaporean public hospitals with the support from politicians, physicians, and patients. Politicians benefit from reduced healthcare costs and enhanced international reputations, physicians see reduced screening workloads, and patients receive results within one hour instead of weeks (Miller, Gomulya, Rao-Kachroo, 2024). Singapore scientists and physicians decided not to use the available Google AI-medical devices for DR and develop their own devices. They worked very hard and made sure AI were used in the initial stage while physicians were in the final stage of decision-making process. With the support of government funding in public hospitals, they can refine the process, and successfully gain the support from physicians, politicians, and patients. Later they established a company (SELENA) to take care of all financing, administrative, and education details in hospitals in Singapore.

SELENA's success in Singapore led to its adoption in African countries for DR grading. They encounter many challenges when they implement these devices in the healthcare systems with scarce resources and poor infrastructure is very challenging. In countries with a few trained doctors, scalable AI-backed medical consultants will be viewed as an alternative option. Inexperienced medical professionals might operate these AI systems and send urgent diagnosis results to experts abroad. Challenges in lower- and middle-income countries include a shortage of screening sites, staff, and equipment; insufficient funding and trained staff; poor telecommunication; AI

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performance degradation; no appropriate treatments after AI tests; and a lack of support services like education and counseling.

Alami et al., (2024) study the adoption of 87 AI technology based initiatives in a Canadian hospital, through interviewing 29 participants during March to July, 2021 by using NASS framework. They find that these are enabling factors and conditions:

a supportive organization culture and leadership leading to a coherent organizational innovation narrative;

mutual trust and transparent communication between senior management and frontline teams;

the presence of champions, translators, and boundary spanners for AI able to build bridges and trust;

and the capacity to attract technical and clinical talents and expertise (page 1).

They also address these constraints and barriers:

contrasting definitions of the value of AI technologies and ways to measure such value;

lack of real-life and context-based service;

varying patients' digital and health literacy capacities;

misalignments between organizational dynamics, clinical and administrative process, infrastructures, and AI technologies;

lack of funding mechanisms covering the implementation, adaption, and expertise required;

challenges arising from practice change, new expertise development, and professional identities;

lack of official professional, reimbursement, and insurance guidelines;

lack of pre-and post-market approval legal and governance frameworks;

diversity of the business and financing models for AI technologies;

and misalignments between investors' priorities and the needs and expectations of health care organization systems (page 1)

When AI is designed for specific functions in a particular context with high accuracy and precision, humans need to collaborate closely with AI to enhance overall performance. AI-enhanced medical devices from developed countries often require extensive training before they can be effectively used in developing countries. Rajesh et al., (2023) emphasize the importance of understanding the local deployment of AI devices for detecting diabetic retinopathy (DR). They said, "these algorithms may be cost-effective in estimation studies, but the complex billing requirements and variability across health care systems make the true costs difficult to estimate. Finally, these algorithms have variable performance across different data sets and need to continue to show equitable diagnoses and outcomes with deployment in a clinical setting. Ultimately, AI devices may significantly reduce the screening burden of DR worldwide, but additional knowledge gaps need to be addressed to ensure the effective use of this new technology." Issues such as data quality, harmonization among healthcare systems, and the reimbursement of scanning expenses also impact the cost of using AI for detecting DR (diabetic retinopathy). For example, different hospitals may use different X-ray machines, which reduces the effectiveness of the same AI devices. Generally, many AI devices present and utilized in healthcare originate from countries with extensive expertise and resources. When AI devices are presented as augmenting rather than replacing doctors, they gain more trust. In countries with scarce resources and a shortage of doctors to support these devices, people may develop automation biases and trust these devices without much scrutiny, assuming comparable success in developed countries guarantees similar results

Thus, the effectiveness of AI systems in healthcare solutions depends on the local context, existing norms, clinical practices, and the demographic characteristics of the patient population. Scaling up AI systems designed to solve specific problems requires attention to deployment

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modalities, model updates, regulatory systems, system variations, and a reimbursement environment (Bajwa et al., 2021). AI health care solutions must be tested in their local system to achieve economic, clinical, and statistical validity. Innovative AI ideas must undergo clinical trials, FDA tests, insurance reimbursement processes, regulatory reviews, and address equity concerns before integration into local workflows (Norman and KFF Health News, 2024). More research is needed to understand how these well-performed AI medical devices available in the market function in different systems (Askin et al., 2024; Jin et al., 2024). Additionally, AI medical devices must address challenges related to data privacy, regulatory compliance, and ethical considerations (Singh, 2024). Thus, many social, economic, and political factors of implementing AI-medical devices in the local context must be addressed.

RESPONSIBLE AI from the SUPPLY SIDE

We need more responsible AI than the performance of AI (Dignum, 2021). Stakeholders, including technology providers, legal, government, professional organizations, venture capitalists and academic institutions need to counterbalance the power of dominant superstar technology companies and seriously recover our core human such as mercy, dignity, and genuine human connection in the AI-driven world (Russell, 2022; Tasioulas, 2022).

Technology providers need to provide explainable, transparent, and responsible algorithms, foundation models, and application models to users (Dignum, 2022). They need to disclose their ethical principles in the development and implementation of AI-medical devices with real-life and context-based evidence. They need to construct and design safe AI first and determine the goals first before the design. Russell (2019, 2022, and 2024) urged the development of safe AI rather than AI-safe culture. They must be accountable for those automatic decision processes and not lead users to have automation biases. For example, they need to increase the trustworthiness of data quality being used for training AI foundation and application models when a small group of private technology sectors exert control over the AI foundation models (Bommasani, Hudson, Adeli et al., 2023; Maslej et al., 2023; Sendak et al., 2020). Foundation models are trained on broad datasets that contain not only statistical/computational biases but also human and system biases. Often, the data for training focuses on statistical/computational biases while ignoring historical human and systemic biases. For example, foundation models are frequently trained on data obtained from white people in developed countries, embedded in their values. The complex layers of these algorithms are not explainable and transparent to users. The defects of the foundation model are inherited by application models in the healthcare system, leaving users unable to understand how the AI system functions or fails. The foundation model can exacerbate social inequalities and fail to adapt to the multimodality of scanning equipment, new experimental technologies, or settings. Suppliers rarely report data quality assessments when presenting their model performance (Sendak et al., 2020). The Center for Research on Foundation Models must continuously urge developers to disclose data quality such that they can report transparency index scores (Bommasani et al., 2024). There is no standardized data quality framework for similar AI-medical products (Rajesh et al,, 2023; Sendak et al., 2020). When a small group of private technology companies control the AI foundation models, it can reinforce existing power structures and worsen conditions for laborers (Crawford, 2021). These companies can easily shift their liabilities to humans involved in AI-augmented decision-making process (Tschider, 2023).

Our current legal, economic, social, and political institutional development must have to catch up with the rapid changes of AI technology. They need to provide standardized data quality frameworks for similar AI-medical products, and official professional, reimbursement, and insurance guidelines. Although the WHO (World Health Organizations), EU, and United Nations have issued responsible AI guidelines, various responsible AI policies in each country are emerging and still cannot give sufficient guidelines to healthcare organizations. Policy makers need to leverage the resources provided by the World Health Organization (WHO) to develop safe and

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equitable AI ecosystems. They should create regulatory and policy mechanisms to ensure AI devices interoperability among healthcare systems, invest in infrastructure in low- and middle-income countries, and decrease AI biases. Structural conditions for successful AI integration include regulatory and governance framework, data governance, cybersecurity strategies, up-to-date infrastructure and equipment, funding models, training for service providers, and also interprofessional collaboration.

Policy-makers and regulators are recommended to introduce all technical, social, economic, and scientific dimensions of AI systems in society (Bommansani et al., 2023) through the following five key tasks: clarify what AI is and focus on actual risks and opportunities (i.e., demystification); create a functional ecosystem to make AI work (i.e., contextualization); involve diverse stakeholders from civil society to address relevant values and interests affected by the use of AI technology (i.e., engagement); develop a directive framework (i.e., regulation); and engage wisely with other global actors (i.e., societies) (Sheikh et al., 2023).

Venture capitalists' investment priorities must match the needs and expectations of healthcare organizations and systems. Sometimes venture capitalists perceive those hospital data can be easily used for training AI without considering hospitals' obligations to their patients (Alami et al., 2024). Politicians may be allied with venture capitalists and overestimate the effectiveness of short-term AI results and underestimate the consequences of AI results at the expanse of privacy of individuals.

Many talented scientists prefer to work in the industry rather than academic area (Bommasani et al., 2024) and pursue more short-term interests (Klinova, 2024). Academic research institutions must take up their serious roles as influences and gatekeepers for patients when they are involved in the AI-medical devices research and seek for higher academic ranking.

TRUST from the DEMAND SIDE

The previous successful cases of implementing imaging AI devices in the public hospitals in Hong Kong and Singapore illustrate the importance of the presence of champions, translators, boundary spanners, technical and clinical talents, and expertise when they want to develop or transfer some mature AI-imaging devices in their health care system. Hospitals need to access funding mechanism covering implementation, adaptation, and expertise. When the new devices are implemented, they disrupt the organizational routine and professional interpretations of their identities. Leaders need strategic alignment between organizational-administrative processes and AI technologies, achieve a consensus on shared values among stakeholders, change the bureaucratic acquisition processes for the short-life cycle of AI technologies, and provide financial incentives and expertise, such as digital technology lawyers and insurance guidelines, to implement changes (Alami et al., 2024, Greenhalgh et al., 2017). AI technology requires organizational adaptation and presents challenges like conflicting professional values between high-quality care and reduced personal interactions, and asking patients or caregivers to interact with evolving technology, leaving them less time for self-care. Changes in service delivery challenge the values of health care providers and patient-clinic relationships. When the acquisition process focuses solely on the lowest price in the tender process, hospitals may end up paying more to update their software or risk using outdated software. In addition, many new technologies may not be compatible with existing AI devices, and also many AI products are not comparable and operable across different hospitals or health care systems (Sendak et al., 2020). Thus, hospitals need to have continuous education, development, questioning, and collaboration among their internal and external stakeholders in the process of integrating AI devices in the existing changing system. They also need to increase patients' digital and health literacy capabilities. They must develop new ways to measure the values of AI and clearly communicate the values to investors, politicians, physicians, nurses, and patients. In summary, they must develop supportive organization culture that supports experimenting different alignments between organization dynamics, clinical, and administrative processes,

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infrastructure, and evolving, short-term AI technologies with resilience. They keep on adjusting their functioning before, during, or after changes to sustain operations (Nemeth et al., 2008). AI practices can be easily diffused in well-led organizations with flat hierarchies, developed decision-making processes, slack resources, a risk-taking climate, and high absorptive capacity.

Conclusions

The adoption and implementation of AI in the global healthcare system is still in its infancy. On the supply side, developers, start-ups, large medical device companies, government, academic research institutions and venture capitalists need to provide responsible AI and show willingness to be responsible for the negative impact of AI on patients in the long-term perspectives. On the demand side, healthcare organizations must know how to experiment with various AI in their evolving systems with feedback and learning. The integration of AI in healthcare system is still in the learning process. More and more hospitals need to share their experience and collaborate with various internal and external stakeholders to increase their trust in the AI system. They must keep on innovating their organizational capacity, accessing sufficient funding, and increasing organization resilience.

Thus, healthcare organizations in developed countries need to align organizational processes and infrastructure with AI technologies, increase capacity by cultivating and empowering champions for AI products, simplify service delivery, and train stakeholders. They frame the value of AI deployment clearly to politicians, physicians, and patients.

These are some future research questions:

1. What are the impacts of the new AI models in healthcare and service delivery on various stakeholders, including patients, caregivers, and physicians?
2. What innovative remuneration and funding models are emerging for AI in the global healthcare system?
3. How do venture capital systems influence the lifecycle of AI-based startups, small to medium enterprises, and healthcare organizations?
4. How should healthcare organizations approach data sharing with AI companies? What should robust data governance models look like in global healthcare organizations?
5. How can stakeholders critically examine the biases and social prejudices embedded within AI foundation models and algorithms?

AI is a social technical system. The integration of AI in hospitals is an on-going negotiation and collaboration process among different stakeholders. The trustworthiness of service providers needs to be increased by their accountability, responsibility and transparency practices. Leaders in the social, political, and legal arenas need to take up more responsibility about the use of AI in the public by developing sound governance structure, consistent responsible AI-policy, and long-term value perspectives. Healthcare organizations are encouraged to increase their capacities for the integration of AI in their system with right champions, organization learning, funding mechanism, political support, and organization resilience.

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