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RESEARCH ARTICLE

The Role of Interorganizational Relationships in the Adoption of Chest X-ray Artificial Intelligence Innovation in Thai Public Hospitals: Multiple Case Studies

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Abstract
This article explores the characteristics and roles of interorganizational relationships (IORs) in promoting the adoption of chest X-ray interpretation artificial intelligence (CXR-AI) innovation in public hospitals. The main research question is, "*What are the characteristics and roles of IORs that influence the adoption of CXR-AI in Thai public hospitals?*" This study employed a qualitative, multiple-case study research method. Six public hospitals in Thailand that adopted CXR-AI innovation were selected as cases, varying in terms of sources of innovation and hospital types. Data were collected through in-depth interviews using a semi-structured questionnaire with 28 key informants involved in the adoption process. The study found that resource-scarce hospitals can mobilize the resources necessary for AI adoption through formal networks. Supplier-client relationships with outsourced IT services provide ideas, technical support, and funding for CXR-AI development. They also functioned as system integrators, linking hospitals to the existing CXR-AI services. Interpersonal relationships may strengthen into more formal R&D collaborations, facilitating the transfer of external knowledge into hospitals. Furthermore, the organizational proximity of collaborating partners can support CXR-AI development projects by reducing obstacles in the medical data-sharing process. However, the influence of interpersonal relationships and proximity varies based on the source of innovation rather than the hospital type. Understanding the influence of IORs as initial conditions for hospitals could help policymakers design measures to improve a hospital's access to essential innovations. Also, by establishing networks between hospitals and external government agencies, early adopters and innovators can create opportunities to steer resources and knowledge to hospitals in need.

Keywords
interorganizational relationships, artificial intelligence, chest X-ray, innovation adoption, Thailand

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Introduction

Thailand's public health system is currently under pressure to improve patient care efficiency by adopting technology. The aging population issue in Thailand is projected to escalate the country's healthcare expenditures by threefold from 539-633 billion Thai baht in 2017 to 1,407-1,854 billion Thai baht in 2032 [1] (Thailand Development Research Institute, 2018). This forecast underlines the imperative for early detection of disease to mitigate healthcare costs. Furthermore, the scarcity of specialized medical professionals has challenged the quality of healthcare service delivery. For instance, it is estimated that at least five million chest X-rays are generated annually solely from routine health check-ups, while only approximately 2,000 radiologists are available to read these scans. Consequently, a significant portion of chest X-ray interpretations are not performed by specialized radiologists (Ingviya, Intajag, Kansomkeat, & Thanomkeat, 2022), which may result in misdiagnosis or even missed diagnosis. A shortage of specialized medical professionals also exacerbates the workload burden for X-ray interpretation. This was especially the case during the Thai Covid-19 epidemic, as evidenced by reported cases of burnout among Thai healthcare practitioners (Somboonviboon, Wittayawisawasakul, & Wacharasint, 2023).

These issues highlight the need to implement supportive technology to reduce the workload of clinicians. Artificial intelligence (AI) has strong potential to greatly reduce the need for humans to perform repetitive tasks. In Thailand, various types of AI have been applied to public health services. For example, since 2018, Google has collaborated with the Department of Medical Services (DMS) under the Ministry of Public Health (MoPH) to develop AI for diagnosing diabetic retinopathy. In treatment planning, Chulabhorn Hospital has been piloting the AI "Watson for Oncology" for cancer treatment pathways, starting in 2020. Chulalongkorn University developed the AI "DeepGI" for detecting abnormal polyps in the colon, and this tool has been tested on Thai patients, starting in 2021. Additionally, recent advancements in digital vision have helped tackle complex challenges in medical image analysis, including the interpretation of chest X-rays (CXR) (Akhter, Singh, & Vatsa, 2023). In Thailand, the chest X-ray artificial intelligence (CXR-AI) technology is increasingly being adopted in Thai public hospitals to aid in diagnosing diseases of the lung, e.g., tuberculosis, lung cancer, Covid-19 pneumonia, etc. (Kaweekijmanee & Chotchakornpant, 2024). Along with other cutting-edge medical image diagnosis technologies, CXR-AI has been identified as a flagship technology in the Six-Year National Action Plan on Artificial Intelligence for the Country's Development (2022-27) adopted by the Thai government in 2022 (MHESI & MDES, 2022).

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[1] As of January 24, 2025, one United States dollar is worth 34 Thai baht. Source: Bank of Thailand, 2025.

Recently, there has been an uptake in debates among academics and communities of healthcare professionals about the benefits of utilizing AI to assist in medical image interpretation. However, existing research may not fully reflect current perceptions, which appear mixed. For example, the study by Ingviya, Intajag, Kansomkeat, and Thanomkeat (2022) suggested that CXR-AI be utilized as a triage tool to pre-screen images before radiologist consultation. This approach could alleviate the workload of radiologists and general physicians while also providing potential economic advantages by reducing labor costs and saving time. Similarly, Tangjai (2020) found a high level of acceptance of radiology AI among professionals and educators in Thailand, while the generation of aging workers remained skeptical. In response, Thai radiology professional communities have begun developing measures to support AI adoption in the field. For example, in 2021, the Royal College of Radiologists of Thailand (RCRT) introduced guidelines for the procurement and utilization of AI systems in radiological diagnosis and, subsequently in 2023, launched a set of standard operating procedures for testing AI in screening for pulmonary tuberculosis in chest radiographs.

CXR-AI has proven highly beneficial in assisting chest-related disease diagnosis. To further promote the adoption of this technology, it is necessary to understand the factors influencing its adoption. The accelerating trend in the adoption of AI-based innovations in the healthcare sector has started to receive increased attention from scholars. Previous studies have explored various factors influencing AI adoption, including individuals' intentions and perceptions (Frank et al., 2021; Laï, Brian, & Mamzer, 2020), cultural perspectives (Krishnamoorthy et al., 2022), and technological aspects (Morrison, 2021; Trivedi & Patel, 2021). Some research has highlighted the importance of both organizational and environmental factors (such as Petersson et al. (2022) and Strohm, Hehakaya, Ranschaert, Boon, and Moors (2020)). However, the role of interorganizational relationships (IORs) among different entities within the environment *vis a vis* AI adoption has yet to be adequately addressed.

Exploring IORs is critical for understanding the conditions conducive to successful innovation activities, thereby enhancing efficiency and improving the quality of service delivery in the Thai public healthcare system. IORs have the potential to facilitate knowledge integration and exchange, thereby increasing the likelihood of innovation (Alexiev, Volberda, & Van den Bosch, 2016; Shu, Page, Gao, & Jiang, 2012). They also provide access to new methods, services, and ideas (Osborne & Flynn, 1997) and allow hospitals to learn faster at less cost and risk (Cullen, 2018). These attributes are particularly relevant for medical AI adoption, which requires multidisciplinary collaboration and interoperability across diverse health data systems. Given that AI is still emerging in Thailand's public health sector, adopters (typically innovators or early adopters) are more risk-tolerant (Rogers, Singhal, & Quinlan, 2014) and embrace innovation despite the uncertainty surrounding the process. Under such uncertainty, external input through

IORs plays a crucial role in driving innovation adoption (Iacono, Martinez, Mangia, & Galdiero, 2012).

To this end, this study qualitatively explored the features of IORs in driving the adoption of CXR-AI in Thai public hospitals. The main research question is: "*What are the characteristics and roles of IORs which influence the adoption of CXR-AI in Thai public hospitals*?" This study explored the characteristics of IORs, the resources mobilized, and the mechanisms behind adoption. The findings of the study should contribute to the literature on innovation adoption, which often focuses on technology, organization, environment (largely due to Baker (2012)'s popular technology, organization, and environment (TOE) framework) and individual perceptions. The insights could benefit policymakers and hospital managers in better-utilizing IORs for promoting the adoption of AI or other related innovations in hospitals to enable the delivery of more effective, efficient, and safer healthcare to patients.

Objective

To explore characteristics and roles of IORs in supporting the adoption of the CXR-AI by using public hospitals in Thailand as case studies.

Literature Review

This section reviews the characteristics of IORs that facilitate innovation adoption and, in particular, AI in public health sector. Interorganizational relationships (IORs) refer to the relationships or connections between and among organizations (Cropper, Ebers, Huxham, & Ring, 2008). IORs may include formal and informal collaborations such as networks, partnerships, strategic alliances, coalitions, cooperative arrangements, and collaborative agreements (Najafian & Colabi, 2014). In this study, the author conceptualized the innovation adoption process as comprising three non-stepwise stages: development, initiation, and implementation. According to Rogers' diffusion of innovation (DOI) theory (Rogers, 2003), initiation (identifying organizations' agenda and matching innovation to the agenda) and implementation are key phases of an organization's innovation adoption process. The development stage may also be considered when an organization creates its own innovation. This study focused on how IORs mobilize resources—data, knowledge, finance, technology, and personnel—to support these processes. These characteristics may occur simultaneously and are not mutually exclusive.

Features of IORs which Promote the Adoption of Innovation

Given the above discussed framework, based on a review of the literature, key features that facilitate innovation adoption include networks, formal linkages, interpersonal elements, and partner proximity.

The first feature of IORs is network. To acquire resources necessary for digital transformation, hospitals may engage in a formally-organized network aimed at achieving specific goals, such as acquiring access to distinctive and potentially complementary resources (Hearld & Carroll, 2016). Such a network may be recognized in terms of objectives or tasks to be achieved. For example, learning networks are concerned with transfer or sharing of knowledge of best practice among hospitals and guide specific investment decisions (Musiolik, 2012). In political networks, actors share norms, beliefs, and a political agenda, and aim to influence the institutional set-up (Bergek, Jacobsson, & Sandén, 2008). Linkages within networks can influence innovative capability and adoption of innovation among hospitals in various ways (Goes & Park, 1997). For instance, administrative links, such as management contracts with IT service providers, can improve interorganizational coordination, and transfer managerial competence while still maintaining the autonomy and flexibility of the partner hospitals (Provan, 1984). Linkages allow hospitals in networks to share resources through planned or unplanned exchange of human resources, provision of training, finance, facilities, or information (Wiewel & Hunter, 1985).

The second feature is formal linkages. Examples may include technological agreements and research and development joint ventures. Organizations may collaborate formally with other organizations in order to innovate. Organizations which plan to innovate may either partner within or beyond their supply-chain (Tether, 2002). Partnership with suppliers and customers within a supply chain enables organizations to transform standard market transactions into more sustainable strategic partnerships based on mutual trust. This collaboration provides deeper insights into customer needs and grants access to innovative and potentially customized solutions from suppliers. Beyond the supply chain, partnerships can also involve competitors, universities, and other research or knowledge-brokering institutions (Haus-Reve, Fitjar, & Rodríguez-Pose, 2019).

The third feature is interpersonal elements. Generally, the development of medical AI applications requires multidisciplinary collaboration between medical specialists and data scientists, consisting of both formal and informal components of collaboration. In this regard, interpersonal aspects in partnerships can strengthen connections among collaborators, enabling the sharing of sensitive information and relevant advice regarding AI adoption. Also, increased trust in partners reduces the uncertainty inherent in innovation processes (Ceci & Iubatti, 2012). Pre-existing relationships with embedded trust between partners can also be a reason for initiating and continuing the collaboration (Pittayasophon & Intarakumnerd, 2015).

Furthermore, interpersonal communication among innovation stakeholders can deliver influential messages that shape strongly held views and drive adoption decisions (Rogers, 2002). Communication may also uncover unexpected messages and enable individuals to express opinions, which can minimize conflict and foster innovative organizational development

(Chutivongse & Gerdsri, 2011). This is especially relevant for the decision to adopt AI in healthcare settings which is characterized by inherent ambiguity and uncertainty in using the system (Petersson et al., 2022).

The last driving feature is proximity of innovating partners. This is especially relevant when the source of innovation is the joint development between the adopter organization and its partner. Research shows that co-locating researchers and business users (the so-called physical proximity) can enhance the development of deep learning research clusters, attributed to the transmission of tacit knowledge (Iacono et al., 2012) and integration of ideas from multiple disciplines (Klinger, Mateos-Garcia, & Stathoulopoulos, 2021). Another type of proximity is organizational proximity. This is the proximity between members of a firm with multiple subunits and with common understanding of firm specific routines (Schamp, Rentmeister, & Lo, 2004). This implies similar organizational context of interacting partners which facilitate mutual understanding and support their collaborations (Knoben & Oerlemans, 2006). Organizational proximity can enhance potential for the collaborating partners to combine information and knowledge and enable transfer of tacit knowledge and sharing of non-standardized resources among them (Burmeister & Colletis-Wahl, 1997).

IORs and the Adoption of AI in the Healthcare Sector

The literature explores the influence of IORs on AI adoption in healthcare from several perspectives. First, collaboration through IORs ensures standardization of methodologies and data, enhancing technical compatibility for AI model development. Therefore, strategies for AI model development should involve data collection from multiple sources, requiring cooperation among research groups, medical institutions, cities and even countries (Belić et al., 2019). Second, collaboration fosters interoperability, enabling systems to exchange and effectively use shared data (Lehne, Sass, Essenwanger, Schepers, & Thun, 2019). Such collaboration should exist starting in the system design stage, and should span across multiple entities that possess dispersed and siloed healthcare data, e.g., hospitals, clinics, nursing homes, pharmacies, testing laboratories, AI service providers, and EHR providers (Davenport & Glaser, 2022; Singh, Hom, Abramoff, Campbell, & Chiang, 2020; Winter & Davidson, 2019). A lack of interoperability would prevent AI applications from reaching their full potential, thereby slowing the advancement of medical treatment (Lehne et al., 2019). Third, information asymmetry between healthcare professionals and AI developers may cause reluctance in adoption (Haider, 2020). This highlights the need for collaborative relationships between adopters and IT providers (Sun, 2021). Lastly, collaboration is essential to promote policies in the healthcare sector, to secure funding from investors, to investigate hospital applications, and to increase the popularity of intelligent healthcare (Xiang et al., 2020).

Given the above discussion, the existing literature on AI in healthcare primarily highlights the importance of IORs in the adoption of AI in public health institutions. However, the published research has yet to explore the mechanisms through which IORs influence adoption across different types of hospitals with varying sources of innovation, particularly in the context of developing countries. These aspects can only be thoroughly examined through qualitative, multiple, case-study research. A conceptual framework for this study is shown below.

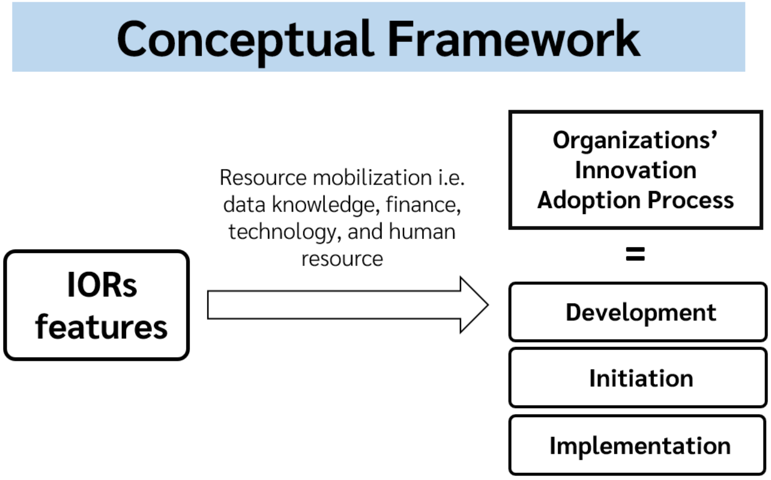

Figure 1. Conceptual Framework

Methodology of the Study

Research Design

This study employed a qualitative research method which is appropriate for exploring a research question that is investigative and open-ended. This method also enables researchers to understand the context or environment in which study participants engage with a problem or issue (Creswell, 2013). The method is especially relevant for emerging issues that have not yet gained widespread attention, such as the adoption of AI in public health in Thailand.

Case Selection

This study employed a multiple, case-study approach to enable cross-case comparisons across different cases and contexts, and support theory building (Yin, 2009). The unit of analysis is the Thai public hospital which has adopted CXR-AI. Cases were selected using an intensity sampling strategy to ensure relevance, representativeness, and comparability. These cases were chosen based on the prolonged adoption of CXR-AI, allowing for meaningful insights to be drawn. To assess the academic significance of each case, the primary author consulted experts and key stakeholders involved. The study selected six cases which vary in terms of sources of innovation (joint development with external actors and adoption from external source) and type of hospital. Characteristics of selected hospitals are shown in Table 1.

Table 1. Summary of Characteristics of Study Hospitals

Characteristic	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Hospital Type	University-Affiliated Hospital	Public Specialized Cancer Hospital	General Hospital	Regional Hospital	Community Hospital	Community Hospital
Affiliation	MHESI	MoPH, DMS	MoPH, Office of the Permanent Secretary	MoPH, Office of the Permanent Secretary	MoPH, Office of the Permanent Secretary	MoPH, Office of the Permanent Secretary
Location (region)	Bangkok	Northeast	Western border	Central	Southern border	Northeast
Rural/Urban	Urban	Semi-urban	Urban	Urban	Rural	Semi-urban
Number of Beds	1,263	120	340	597	30	30
Number of Staff	11,476	380	830	1,289	194	155
Available Radiologists	Yes	Yes	Yes	Yes	No	No
Adopted CXR-AI	Government-funded and developed Covid-19 pneumonia CXR-AI	Government-funded and developed CXR-AI	Commercially developed CXR-AI	Commercially developed CXR-AI	Commercially developed CXR-AI	Government-funded and developed CXR-AI
Year of Data	2022	2022	2022	2022-23	2022	2022

Compiled by the authors based on data for the years 2022-23 from the MoPH, hospital annual reports, and hospital website. Notes: MHESI = Ministry of Higher Education, Science, Research and Innovation, MoPH = Ministry of Public Health, DMS = Department of Medical Services

Data Collection

This study collected data through in-depth interviews (IDI) with 28 key informants using a semi-structured questionnaire. Interviewees (see Table 2) were stakeholders involved in the process of development or implementation of CXR-AI innovation in a public hospital. The study employed purposive sampling (Tashakkori, Johnson, & Teddlie, 2020) for selecting IDI respondents for each case, and also relied on snowball sampling to collect data from additional key informants based on previous respondent recommendation. This study was part of a doctoral dissertation which focused on factors influencing the adoption of AI innovation. Thus, the primary author asked open-ended questions about the process of AI adoption, drivers, and barriers to adoption of AI. The IDI took place during February to July 2023. IDI were conducted individually except for a regional hospital (Case #4) where the radiologist and the radiographer preferred to participate together. Each IDI took 30-120 minutes, depending on how much the interviewee had engaged in the case. The IDI were audio or video recorded subject to the participant's consent, and then the content was transcribed orthographically into text.

Table 2. Summary of Key Informants in Each Case

Case #	Source of CXR-AI	Hospital Type	IDI Key Informant
1.	Joint development	university-affiliated hospital	head of the department of radiology, faculty of medicine radiologist data science professor computer engineering professor data engineer
2.	Joint development	specialized cancer hospital	hospital director former hospital director hospital deputy director computer engineering professor oto-rhino-laryngologist radiographer IT manager
3.	External source	standard-level hospital	hospital deputy director radiologist IT manager chief executive officer of CXR-AI service provider chief operating officer of CXR-AI service provider *
4.	External source	advance-level hospital	hospital assistant director radiologist nephrologist radiographer chief operating officer of CXR-AI service provider *

Table 2. Summary of Key Informants in Each Case

Cases	Source of CXR-AI	Hospital Types	Key Informants
5.	External source	community-level hospital	hospital director general practitioner IT manager IT officer chief operating officer of CXR-AI service provider *
6.	External source	community-level hospital	hospital director radiographer IT officer

*Note: Chief Operating Officer of AI service provider * is the sameperson across cases 3-5.

Data Analysis

The primary author conducted thematic analysis of the IDI transcripts, and explored themes related to IORs. This step was facilitated by using ATLAS.ti 23 software. The results of the analysis are a synthesis of insights provided by the software and the primary author's own judgement.

Ethics

Ethical approval for the study protocol was obtained from the Ethics Committee in Human Research, National Institute of Development Administration [Reference Number: COA No. 2023/0004].

Findings

Four themes of IORs were found to promote the adoption of AI in public hospitals in Thailand. As shown in Table 3, the four themes include 1) network membership, 2) supplier-client relationships, 3) interpersonal elements, and 4) proximity of partners.

Table 3. Summary of Four Themes of IORs

<table>
<tr><th>Case #</th><th>Network Membership</th><th>Supplier-Client Relationships</th><th>Interpersonal Elements</th><th>Proximity of Partners</th></tr>
<tr><td>1 - university-affiliated hospital</td><td>N.A.</td><td>IT outsourcing as a source of innovation
Pre-condition of business partnership</td><td>Channel for recruitment of the research team
Pre-condition of business partnership</td><td>Organizational proximity of partners</td></tr>
<tr><td>2 – specialized cancer hospital</td><td>N.A.</td><td rowspan="5">IT outsourcing as a linkage to the CXR-AI service</td><td>Channel for recruitment of the research team</td><td>Organizational proximity of partners (exists but ineffective)</td></tr>
<tr><td>3 - standard-level hospital</td><td>N.A.</td><td rowspan="4">Interpersonal communication with the innovators or early adopters</td><td>N.A.</td></tr>
<tr><td>4 - advance-level hospital</td><td>N.A.</td><td>N.A.</td></tr>
<tr><td>5 - community-level hospital</td><td rowspan="2">‘Chalerm Phra Kiat’ hospital network as a learning and political network
Resource mobilisation</td><td>Isolation from technological and knowledge actors</td></tr>
<tr><td>6 - community-level hospital</td><td>N.A.</td></tr>
</table>

Network Membership

In the context of Thailand, community-level hospitals are small hospitals, and normally resource scarce. Community (i.e., district) hospitals in Cases #5 and #6 belong to a formally organized group of community hospitals called “Chalerm Phra Kiat” hospital network. Hospitals in this network have the mission to deliver best practice in management and quality improvement comparable to international standards, and to enhance the accessibility of healthcare services for the catchment-area population.

In this network, member hospitals shared a common agenda in leveraging digital technology to solve health issues in their respective catchment area. The shared agenda had been delegated to the hospital’s digital strategy and culture, which later facilitated the adoption of the advanced digital technology, e.g., CXR-AI.

> "*Being designated a 'Chalerm Phra Kiat' hospital made the adoption of* (CXR) *AI smoother than other hospitals because we have a* (supporting) *policy. . . . Other community hospitals have limited resources and do not have a supporting strategy to trigger (*the adoption*). So, they face a barrier of adoption. . . . If we were not a 'Chalerm Phra Kiat' hospital, even if we had more available resources than this, but without this purpose, we would have spent that money on something else*." (hospital director, Case #6)

> Participation in this network enhanced a hospital's privilege in receiving resources from a prestigious external actor, e.g., a charitable public health-related foundation under Royal Patronage. The additional technology resource is crucial for laying the basic IT foundation for the hospital prior to AI adoption.

> "*The Foundation supports us, so we are advantaged over other hospitals. The support includes trainers and technology*." (hospital director, Case #5)

> "*Being designated as a 'Chalerm Phra Kiat' hospital made a difference for us. We received trust and special care from the Foundation*." (general practitioner, Case #5)

By contrast, an IT officer in a community hospital (Case #5) shared that a neighboring hospital outside of the Chalerm Phra Kiat Hospital lacked the necessary budget, and was unable to adopt the similar CXR-AI technology.

> *"A neighboring hospital arranged a study trip for key staff to visit us. The visitors asked about the cost of the (AI) adoption, and they were stunned* (to hear our response). Fortunately, we received funding support. Other hospitals saw (this AI) *and also wanted to subscribe, but they lacked budgeting. However, in the future, if the financial support is not continuous, we are not sure if we could continue the subscription.*" (IT officer, Case #5)

Moreover, the network allowed the community hospital in Case #5 to share its success story of digital transformation with the MoPH. This consequently increased its chance of receiving additional support from the MoPH to further drive its digital transformation. Such support allowed the hospital to gain experience in adopting the foundational digital technologies, such as a paperless health information system (HIS) and automated registration kiosk.

Supplier-Client Relationships

For joint-development cases, supplier-client relationships between hospitals and outsourcing IT system providers are a source of ideas, technical support, and funding for CXR-AI development. In a university-affiliated hospital (Case #1), the radiology department of the hospital had an existing relationship with multiple outsourcing software services and medical device firms. These firms later became hospital partners in the development of Covid-19 pneumonia CXR-AI innovation. Before the partnership formation, the department already had established trust among these companies and had insightful information about technical capabilities and their interest. The supplier-client relationships were later elevated to a joint research partnership.

> "*The PACS* (picture archiving and communication system) *company provided support related to Covid-19 in several aspects. The company had provided PACS service to our hospital for many years. We knew what they could do and we knew that we could talk to them. We also knew what they had been doing about Covid-19, such as providing X-ray service to those under quarantine or for patients in field hospitals*." (Head of department of radiology, Case #1)

In other cases, the IT outsourcing firms, such as HIS providers or PACS providers, also acted as a link between the hospitals and the CXR-AI service provider. In one community hospital (Case #5, the hospital's outsourcing HIS provider was collaborating with the CXR-AI service provider in testing the CXR-AI model at an early stage of the development, and invited this hospital to join the project as a test site. Thus, the hospital had an opportunity to trial this technology free of charge. Similarly, in another community hospital (Case #6), its PACS vendor also introduced a user-friendly version of CXR-AI to the hospital managing director. Business partnerships between the CXR-AI providers and hospital HIS/PACS providers were crucial for building interoperability between different IT systems. However, in one general hospital (Case #3), a lengthy process of partnership formation between the AI and PACS vendors (due to internal changes within the PACS company) impeded the integration of the systems, resulting in persistent incompatibility of CXR-AI with existing PACS at the early stage of the adoption process.

Interpersonal Elements

Different forms of interpersonal elements were found to promote the CXR-AI adoption. In the joint development cases (#1-2), researchers and research partners were recruited to the CXR-AI development project through personal connection. In Case #2, the personal relationship and trust between a highly reputable senior radiologist, a head of the CXR-AI project, and its partner hospitals enabled the partners to agree to join the project. One of the business partnerships in the CXR-AI project of a university-affiliated hospital (Case #1) also evolved from a personal connection between a hospital's radiologist, then a manager of this project, and the owner of a software development company.

"*I had a personal connection with the company. . . . I already knew the company's owner so I asked whether they were interested in investing in the AI project*." (radiologist, Case #1)

Moreover, a personal connection between the hospital managers and external early adopters allowed transmission of information about the existing CXR-AI to the hospital. Examples of the early adopters are hospitals which have previously adopted the same CXR-AI product (the general hospital in Case #3 and the community hospital in Case #6) and a key person from Thai Health Tech Association (the regional hospital in Case #4). After being informed of the innovation's existence, the hospital actively sought more information about it before making the AI adoption decision. In the community hospital (Case #6), a partner hospital which was an early adopter of the same CXR-AI model acted as a "buddy" which provided technical advice and guidance on the use of the adopted CXR-AI.

"*Our hospital has academic collaboration with* (this partner) *hospital . . . This hospital has developed CXR-AI. . . . This hospital is also an early user. After we adopted this AI, this hospital gave us advice, being a buddy for us in topics like how to solve* (technical) *problems, and how to contact the vendor*." (hospital director, Case #6)

The case studies also highlight the crucial role of informal mode of communication between the hospital's key decision maker and the CXR-AI service provider via informal channels (e.g., Line application, Facebook messenger, phone call) before the final adoption decision. Such modes of communication led to effective coordination, enhanced mutual understanding in service operation, and minimized managerial obstacle in the implementation process, as shown in a regional hospital (Case #4).

"*I know the chief operating officer* (of the CXR-AI company). I have his Facebook contact and phone number. I always shared with him about problems (of use). . . . *He is very friendly, and we get along well. The complicated process* (of operating the CXR-AI) *became less complex. This became a part of our decision* (to adopt this CXR-AI)." (nephrologist, Case #4)

A hospital's direct communication with the CXR-AI provider allows better transfer of information about the service, minimizes loss of message, and provides direct feedback for improvement to the CXR-AI provider, as reflected by the chief operating officer of the CXR-AI provider:

"*I prefer the user* (hospital) *talking to us directly rather than talking through the PACS vendor. If the message is passed through the PACS vendor, there may be a loss or distortion of the message*." (Chief operating officer of the CXR-AI service provider, Case #3)

Proximity of Partners

The case studies highlight the importance of proximity among partners in supporting the development of the CXR-AI technology. The university-affiliated hospital (Case #1) reported organizational proximity of collaborating partners (faculty of medicine and faculty of engineering) within the same university as a facilitator in developing the Covid-19 pneumonia CXR-AI. As a priority, the head of a hospital's radiology department, a key person of this project, preferred that the composition of the project working group consist of professors and researchers from the same university. This was to minimize obstacles in the medical data sharing process among the researchers under the same university's roof. This would be an advantage over the data-sharing among different universities.

> "*We had concerns about patient personal data sharing. It would be easier to manage patient data within the* (same) *university. Ideally we would prefer a data scientist from our hospital. . . . We attempted to discuss this with the other university, but we found difficulty in data sharing*." (head of department of radiology, Case #1)

Case 2 is different. The public specialized cancer hospital in this case is a specialized facility under the DMS of the MoPH. To develop its CXR-AI, it had to partner with a public university in order to form a multidisciplinary research team. This project also had to recruit other hospitals under the DMS to join the development team. Despite being under the same roof (i.e., the DMS), organizational proximity did not initially encourage participation in the project due to contradicting individual-level perceptions toward the AI tools. Instead, the director of this cancer hospital intervened to persuade the directors of the DMS hospitals to assign their radiologists to join the project.

In Case #5, a small community-level hospital located in a remote area faced a problem of isolation from technological and knowledge actors in the (central) region. This could be a barrier to accessing new knowledge and technology.

> "*The main issue is that our location is far away from the central area, which means we may not have timely access to new information, knowledge, or advancements. Because we are somewhat isolated, we may not be as up-to-date as others who are more centrally located. We do not have as many*

opportunities to explore innovation, like other hospitals in the central region. . ..” (hospital director, Case #5)

Conclusions and Discussion

This study explored characteristics and roles of IORs in promoting adoption of the CXR-AI innovation in Thai public hospitals. An analysis of the findings suggests features of IORs which influence the adoption of CXR-AI, including network membership, supplier-client relationships, interpersonal elements, and proximity of partners. The study also explored the mechanisms through which IORs influence adoption across different types of hospitals with varying sources of innovation.

The findings on the role of formal networks expand on Hearld and Carroll (2016), who argue that hospitals join networks to access unique, complementary resources, especially in resource-scarce settings like community hospitals adopting advanced technology. In the community hospitals in Cases #5 and #6, the Chalerm Phra Kiat Hospital network functioned as a “learning network” (Musiolik, 2012), facilitating the exchange of best practices in digital transformation among its members. Additionally, it served as a “political network” (Bergek et al., 2008), where member hospitals pursued a common agenda of leveraging digital technology to address healthcare challenges in their respective regions. Furthermore, the network comprised resource links (Wiewel & Hunter, 1985) which enabled the transfer of basic digital technologies to the hospitals. The network thus established essential supporting conditions for the integration of more advanced technologies, such as AI, to the hospitals. Other hospital groups did not explicitly report the formal networks’ role in resource mobilization, likely due to non-participation in such networks or reliance on alternative sources.

The role of partnerships with suppliers as a source of innovation for hospitals largely aligns with the proposition by Haus-Reve et al. (2019) that such partnerships can lead to innovative and, potentially, customized solutions. An evolution of collaborative mode from pure market transactions into long-term strategic relationships supported by mutual trust is also evident in this study. The joint development case (Case #1) demonstrated that supplier-client relationships could evolve into business partnerships for the CXR-AI development. Additionally, the HIS or PACS outsourcing suppliers also functioned as system integrators, linking hospitals to the existing CXR-AI services, as seen in all other cases.

Interpersonal relationships are particularly crucial for the adoption of cutting-edge technologies like AI, which involve high uncertainty in development, a high risk of failure, and the potential for undesirable outcomes during implementation. The role of interpersonal relationships is observed in all cases but varies based on the source of innovation rather than hospital type. For the joint-development case, existing interpersonal connections between key persons in hospitals with external partners can evolve into the more formal relationship in R&D

of the AI model. This finding agrees with Pittayasophon and Intarakumnerd (2015) that a pre-existing relationship between partners can be a reason for initiating and continuing the collaboration. A pre-existing close relationship suggests that trust is already an integral part of the connection. The interpersonal elements in the partnership also reinforce the linkages among members, and facilitates the disclosure of sensitive information and advice that is related to the adoption of innovation. The uncertainty that characterizes the innovation processes becomes lowered when an organization's trust in its partners increases (Ceci & Iubatti, 2012). For the cases of the adoption from an external source, interpersonal communication with innovators or early adopters could facilitate the acquisition of knowledge about the CXR-AI innovation from outside the hospital. This finding aligns with the role of interpersonal communication in influencing the organization's decision to adopt an innovation as suggested by other research (Chutivongse & Gerdsri, 2011; Rogers, 2002).

The role of proximity is more pronounced in the case of joint development, an activity characterized by high relational intensity. This process necessitates frequent interaction between knowledge creators and users, facilitating the transfer of tacit knowledge (Pittayasophon & Intarakumnerd, 2015). This process is absent in hospitals without AI R&D projects (Case #3–6). Organizational proximity of the research partners was preferred to ease health data sharing, avoiding managerial barriers which would happen in cross-university collaborations Collaboration is more efficient and yields better results if both interacting partners share similar organizational contexts since they become more capable of transferring resources among them (Burmeister & Colletis-Wahl, 1997). However, organizational proximity may not guarantee the initiation of an innovation project if members under the same organization exhibit contradicting values regarding the innovation in question. Also, in Case #5, the community-level hospital (located in a remote area) faced weak interaction with knowledge and technological actors which constrained interactive learning and innovation (Wieczorek & Hekkert, 2012). Nonetheless, this disadvantage was compensated for by formal linkages with innovators, early adopters, or knowledge and technology actors. Moreover, the growth of online communication tools facilitated access to the knowledge and technology.

Contributions of the Study

In terms of theoretical contribution, this study contributes to the growing knowledge in the field of the adoption of innovation. The study has explored IORs as a factor which influences the adoption of innovation which was previously concerned only with those factors related to technology, organizations, environment, and individual perceptions.

In terms of practical contributions, the findings from this study should help policymakers and hospital managers leverage IORs to advance AI adoption, and enhancing patient care efficiency/effectiveness/safety. First, understanding the role of IORs as a strategic asset for hospitals adopting innovation would enable policymakers to design appropriate measures ensuring equitable access to innovation. Second, the findings offer lessons for strengthening networks among hospitals, government agencies, early adopters, and innovators (e.g., software, HIS, PACS companies) to facilitate resource and knowledge mobilization. Lastly, the study highlights the importance of communication about innovation among potential adopters. Policymakers and medical associations should, therefore, promote knowledge exchange through initiatives like public advocacy programs, and sharing early-adopter digital transformation experience with later adopters.

Limitations and Suggested Future Research

This study may have limitations in terms of generalizability. The study did not include hospitals with other characteristics such as community hospitals without a network membership. The study also investigated only one type of AI technology. Further research should include a larger population of hospitals with different characteristics and different AI systems.

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