(International Print/Online Journal)

SJIF IMPACT FACTOR: 5.565
PUBMED-National Library of Medicine ID-101739732

ISSN (Print): 2209-2870
ISSN (Online): 2209-2862

International Journal of Medical Science and Current Research (IJMSCR)
Available online at: www.ijmscr.com
Volume 4, Issue 5, Page No: 645-652
September-October 2021

IJMSCR

A Literature Review of Health Data Problems: Related to Implementation of Data Science in Thailand Healthcare Systems

Pumin Wimuttigosol*
*Mahidol Wittayanusorn school

***Corresponding Author:**
Pumin Wimuttigosol*
*Mahidol Wittayanusorn school

Type of Publication: Original Research Paper
Conflicts of Interest: Nil

Abstract

Data science becomes recently popular at an unprecedented rate as it provides invaluable benefits for institutions and companies adopted it. In data science, conventional analytics and artificial intelligence have been implemented to analyze the excessive amount of data into systemically organized data used for planning institutes' provision strategies, gaining insights in particular subjects and for other beneficial purposes. Without reliable and valid data, institutions, implemented data science, will be unable to pull out data science full capability. Thus, this paper presents health data problems in Thailand healthcare systems from selected research relevant to problems in Thailand health data with brief background of Thailand health data system and possible impacts of data science in improving healthcare.

Keywords: Data science, HDC, HIS, EHR, Coding

INTRODUCTION

In the twenty-first century, communication and data collection in a digital form has become widely accepted globally. Information technology is being significantly used at an unprecedented rate, and having a major influence in every society[1], thus causing an information bombardment called "information overload"[2]. Likewise, medical institutions have encountered tremendous amounts of data, both in variety and quantity. As such, modern medical devices, computed tomography (CT) scans, and magnetic resonance imaging (MRI) [3] have provided data in the form of images and ultrasonography via videos [4], which has led to more complicated and unstructured data. To address this issue further, electronic health records, diseases information, personnel and management information, and pharmaceutical data have also been comprised in medical institutions' records.

In Thailand, each hospital has different fundamental software for assembling medical information or a Hospital Information System (HIS) [5], but has adopted a standard structure called "43 files" or Health Data Center (HDC). This has functioned as a database for planning national strategies and conducting research [6]. Nevertheless, HDC, nowadays, is still confronted with many obstacles, complexities, and reliability problems, thus rendering it to be used without full capability.

Data science has focused on administrating the three properties of big data: variety, volume and velocity into stratified data [7], as well as applying analytics, particularly artificial intelligence (AI), to interpret the data and formulate the correlation among them, as a consequence, this would enhance the potential to apply the findings for pragmatic application [8], including improving the diagnosis efficiency [9,10].

precision medicine [11], and providing future opportunities for personalized treatment[12].

This literature reviews research related to problems in process of collecting data by looking into problems of selected tools and system in which adopted for Thailand health data. This literature reports practitioners' findings which will be separated into parts of problems, causes and their recommendations or opinion to address the challenges. The solutions provided were based from the published research with some research guideline from specialists.

BRIEF IMPACT OF DATA SCIENCE IN HEALTHCARE

Problems in the Medical Field to be solved by Data Science

Although the technology for physical examinations and medical treatments has substantially progressed, medical devices assisting physicians in treatment decisions, diagnoses, and patients' health assessments have yet to be widely adopted [13].

Diagnostic errors accounted for approximately one-third of all US malpractice claims, and it was estimated that 40,000-80,000 patients died annually that was a result of misdiagnosis. This has cost an unnecessary loss of US $2.6 billion in the past 10 years [14]. There have also been challenges on the overuse of ineffective services and underuse of those which are effective. Medical overuse, including overdiagnosis, over-testing, and overtreatment can be observed in many aspects; such as undergoing mammograms by women with life expectancies less than 10 years although they received minimal benefits[15]. Patients' requests for medication were the most claimed causes of medical overuse and false positives that considerably contributed to drug overuses[16]. Additionally, one finding found that cardiac-related disease screening had low accuracy, thus prompting redundant cardiac stress tests costing around US $500,000 a year in the USA, and exposing many patients to radiation [17]. Underdiagnosed and false negatives have also caused preventable harm among patients, which have failed to provide effective medication in advance [18].

Benefits from the Application of Data Science

In today's world, the application of data science has provided numerous advantages for various fields and industries. For the medical profession, some of these benefits can be stated as follows:

Nowadays, healthcare expenditure mainly emphasizes treatment and therapy instead of prevention. Only 5.9% of the total healthcare expenditure was associated with preventive care in Canada, the country spending the most in proportion [19]. Data science with modern analytics can also provide in-depth insight into the risk factors and biomarkers with accuracy in the early stages, thus reducing expenses related to false-positive authentication via screening [20]. As a consequence, early identification of disease would enable quick responses to prevent the disease from occurring [21].

Assimilating health records has reduced the time spent on collecting testimonies and analyzing research as a health database to enable an easy route for researchers to extract information. This has notably serviced research, especially which has had high dynamic change. For example, research on the evaluation of the cardiac surgery mortality rates: 30-day mortality or a longer follow-up published several years ago would already be inapplicable at present, as the trends would have changed; consequently, they would be unable to be utilized in clinical trials [22].

With more advanced technology detecting more measures, stratifying patients with similar traits could be conducted more precisely, therefore encouraging precision medicine for each group of patients [11]. Genetics has also been taken into account for categorizing cancer and making decisions on specific treatment [23]

Next-generation sequencing (NGS) with a deep learning model has reduced the required time for decoding human genetics and providing in-depth information, which was inaccessible in the past [24]. NGS-based data integrated with electronic health records (EHR) of each individual could raise the expectation for personalized treatment, which would be most compatible with each patient in the future [12]. Moreover, it has been estimated that personalized treatment would extend the global life expectancy by 1.3 years and have an impact on the world's economy of between US $2-10 billion. [25].

Data interoperability can be met by implementing data science. Although a medical central database would be implemented around the world, patients' EHR in

Volume 4, Issue 5; September-October 2021; Page No 645-652

healthcare institutions would not yet be properly linked. Therefore, data sharing between healthcare organizations would be mandatory, as patients could receive healthcare services at multiple institutions, and referrals between healthcare services would also be possible [26]. In addition, Thailand healthcare services adopted a wide range of hospital software [27], creating hurdles for sharing of information. Therefore, an interoperability data set would have importance, which some organizations have already implemented this; such as, Fast Healthcare Interoperability Resources (FHIR) [26].

A BRIEF OF THAILAND HEALTH DATA SYSTEM

Hospital Information System (HIS)

The HIS holds and maintains all of the information related to the institution's health records, medical records, personal health records, including personnel, costs, strategies, and management information [28]. Each healthcare organization would use different software. HOSXP is the most adopted system in government healthcare centers; other software is E-PHIS, EMR soft, SSB, etc. [27].

43 Files (HDC)

This is a standard formation of a medical database system that collects some parts of the medical records in every medical institution in Thailand for studying the population's overall health, as well as planning the national healthcare strategy and policy. The 43 Files or HDC consist of five main files: 1) Cumulative File compiles fundamental information of the patients; such as, PERSON and CHRONIC. 2) Service File contains more about the services the patient has received like DRUG_OPD and CHARGE_OPD. 3) Semi-explorer Service File collects extra information, which is not found in the Cumulative file; such as, LABFU and REHABILITATION file. 4) Policy File collects information about the medical and healthcare policy. 5) DATA_CORRECT File consists of information that needs to be revised [6].

ICD-10

The International Classification of Diseases, 10th Revision (ICD-10) has also been used in the HDC for classifying and grouping diseases. The coding of the ICD-10 is based on the alphabet of A-Z and numerals to resemble the disease type [29].

In Thailand, medical records were first assembled in the level of health facilities using a Hospital Information System (HIS) then some medical records from every medical institution would later be collected into a central database called a Health Data Center (HDC), which works as a database for research and planning national strategies [6].

PROBLEMS OF THAILAND HEALTH DATA

Many medical institutions around the country recently implement research and data science and modern analytics for diagnosis and other beneficial purposes [10]; however, problems in rudimentary basis for supporting data science are conceivable.

This paper distinguishes the problems into 2 main categories based on the order to successfully adopt data science.

1. *Fundamental Element Required for Data Science*
2. *Efficiency of the Elements supporting Data Science*
    a. Correctness of Thailand Health Data
    b. Health Data Punctuality

1. *Fundamental Element Required for Data Science*

Without fully transforming health data into electronic forms, data science will be unable to show its full potential as converting data into applicable forms will be time-consuming.

Cause: Lack of EHR Adoption

EHR and EMR have both been initiated in Thailand and are a paramount infrastructure for supporting the implementation of data science. Nonetheless, Thongthai et al. (2017) discovered that only 28.5% of all dental and medical clinics adopted EHR, and 25.4% of which only used EHR for collecting patients' fundamental information such as, telephone number, name, age, and gender by sending mails with questionnaire to 441 clinics in health region 10. The responders average scores for self-assessment of computer experiences, reduction of expense from implementing EHR, acknowledging EHR benefits, acknowledging convenience of EHR, and eagerness of implementing EHR were 3.95±0.75, 3.63±0.92, 3.84±0.75, 3,65±0.75, and 3.80±1.08 out of 5 in order [30]. In addition, 51-75% of all hospitals have already

Volume 4, Issue 5; September-October 2021; Page No 645-652

applied EHR/EMR for collecting management and administration data, but only 0-25% have applied EHR/EMR for clinical purposes (2017) [31].

Solution: Encouragement

Incentives can encourage institutes to embrace EHR. The USA implemented a regulation called the "Hitech Act" for encouraging medical institutions to adopt EHR through meaningful programs with incentives. [32, 33]. According to Theera-Ampornpunt, these kinds of policies to persuade EHR implementation have yet to be seen in Thailand; therefore, in studying these policies, this may create benefits in constituting a national policy for Thailand in the future. Likewise, government should issue regulations and policies on EHR adoption for quality and efficient health services for the healthcare system [34].

2. *Efficiency of the Elements supporting Data Science*
   a. Correctness of Thailand Health Data

Wang Sam Mo Hospital, Udon Thani province, has concluded the problems found in the HCD. The three main challenges where the information was not completely entered, a lot of information did not use the right standard or code, and the inserted information was not reliable and false. Problems with the incorrect standard code were found in files, such as ACCIDENT, SERVICE, and APPOINTMENT. In the PERSON file, some compulsory information was left blank like status, age, nationality, etc. Some data were also incorrect in the DRUGALLERY file where the 24-digit code was incorrect, and in the SERVICE file, some of the diagnoses were not right [35].

From the inspection of the physicians of Public Health Region 10, the problems unearthed were similar to the former issues, where the identity number (ICD) was incorrect, there was wrong information in the TYPE_AREA file that caused some youth not to receive the services that they should, as well as incorrect data in the ANC and LABOR files, which resulted in some information of pregnant women to show to be pregnant once but in labor two or more times. Some information was also left blank in files like CHRONIC [36]

From the research of the Information and Communication Technology Center, Office of the Permanent Secretary Ministry of Public Health (2017) on the quality of the disease code, the quality of data varied among the public health regions by using DIAGNOSIS_OPD file. In 2015, the percentage errors of Public Health Region 8 were 14.61%, and this was reduced to 12.22% in 2017. Likewise, the overall trend of the data percentage errors was gradually reduced in most regions. Some of the errors were misused of codes between gender and incorrect placing of coding. Every region had errors when inserting the disease code, thus revealing there was a lack of understanding and proficiency on entering data [37].

Habusaya and Ditcharoen (2020) used the C4.5 algorithm and Naïve Bayes to compare the efficacy of detecting the percentage errors of entering the ICD-10 codes and founded that ERROR_CODE=B4, representing the outpatients received the vaccine, had the most errors. The correctness of the data was 90.16% and 89.87% analyzed by C4.5 algorithm and Naïve Bayes in order[38].

   b. Health Data Punctuality

With numerous obstacles impeding the data transmitting process, every step was delayed, including converting the unstructured data into specific code, loading data into the database and amending the error codes. Hence, details and illustrates obtained from the delayed data set reduces credibility [39].

Cause: Staff Knowledge

With respect to Wipak et al.'s research (2017), the personnel responsible for inserting the data into the HCD and their attitude toward collecting data was found to be at a good level; additionally, their knowledge on managing data was at a moderate level (47.83% of the total sample) and performance on inserting data was at a low level(73.92% of the sample) although 58.70% of the responders reported good attitudes toward managing data. Furthermore, only 65.22% of all respondents had experienced systematic training from the survey. With this, experiences and education level were found to have positive correlation with the performance of inserting data at $p<0.05$[39].

Cause: Staff's Instruction, Allocation, and Tools

From the results of the interviews, it was found that inserting data consumed a long period due to the complexity of the platform, use of many windows, instability of the Internet connection, and having other

Volume 4, Issue 5; September-October 2021; Page No 645-652

responsibilities that had to be taken into account, thus causing a delay and incorrectness of sending data to the HDC. Furthermore, insufficient surveillance and leniency discouraged the staff to work effectively plus the policies on coding were ambiguous without clear instruction and often change, confusing the staffs. Software structure also impacted their performance. The complexity and overlapping of the file structure also delayed and hindered them from coding properly [39].

Other problems included insufficient staff who had responsibility; thus, rendering staff expertise in other fields to be assigned additional work in entering the ICD-10 code. Furthermore, many physicians used abbreviations, which could be interpreted into many definitions. Hence, the data were returned for clarification and consumed more time [38].

Solution: Assisting Staffs

Effective tools need to be provided sufficiently to enhance staffs coding capability as well as improve their comprehension on their duty. Vigilance and performance assessment also needs to be done continually [39].

Workshops should be regularly held at the healthcare center for coding-appointed staff to revise their knowledge and catch up with current coding standards if amended. Development on quality coding tools examination strategies and evaluation reliability of the coded data should be inaugurated as well as strategies for systematic and continual coding [37].

Solution: Entrusting Regulations

There is a need for constituting an administration board specifically for developing coding integration process and improving coding reliability, holding the authority to issue strategies, mandates and standard coding guidelines. Furthermore, policy needs to be explicitly announced, addressing all controversial coding conflicts and giving access to examining the coded data conveniently[37].

Staffs need to be specialized in coding or full of experience; otherwise, the percentages error will persist. Frequent monitoring is also compulsory, medical institutes should randomly inspect coded data, such as 3-4 times a year [38].

Implementation to Address Problems

Si sa ket Hospital developed a program called "ICD NAVIGATOR VERSION 6.1.1" to facilitate the coding processes. The findings showed that in using the ICD NAVIGATOR VERSION 6.1.1, the two-year-experienced staff with ICD-10 coding were able to reduce the work for about three minutes and had fewer percentage errors than those using conventional ICD-10 textbooks, improving the overall correctness to 95.0% from 86.7%. Likewise, those four-year-experienced staff used 2 minutes less when using ICD NAVIGATION 6.1.1. and coded more accurately from 88.3% to 96.7% of correctness. The program consisted of many conventional ICD-10 coding textbooks and provided easy access for the staff, reducing coding time and increase reliability [40].

CONCLUSION AND RECOMMENDATION

Data science has begun to play a big role in people's daily life in only several decades, which has reformed people's lives in a way that has been unprecedented from a manual system in the past into the present digital form. Moreover, EHR and other medical data have become more crucial for medical services that would be applied for future purposes by conducting medical research on diseases, manufacturing medicines and vaccines, assisting physicians in diagnosing and choosing medical treatment, and planning future strategies. Nevertheless, the challenges on assembling medical data for achieving these objectives still need to be addressed. Otherwise, data science applications in Thailand will not play many contributions although possible.

First and foremost, health records in the form of electronic need to be fully adopted and urged since this resembles the most rudimentary basis for assembling tremendous data records, which support data science, designated to deal with big data. Issuing policy encouraging hospitals, clinics and other healthcare organizations may address the problems and render faster adoption of EHR. Nevertheless, triumph on establishing a database would not guarantee it's usefulness. With this in mind, the quality of the information inside the HCD needs to be further improved to reduce errors and false data, which would affect the reliability of the demographics, and details received and cause a huge amount of cleaning time. At last, with the delay from various factors, such as cleansing process, examining the credibility, coding

Volume 4, Issue 5; September-October 2021; Page No 645-652

the data and loading data, the process of collecting data does not meet up with the deadline; the analysis received afterward lacks novelty and is not real-time, reducing its value.

REFERENCE

1. Boonprayong W. The challenges of using big data in health. Journal of Vocation and Technical Education 2015;5(10):68-9. http://www.ojs.kmutnb.ac.th/index.php/JVTE/article/viewFile/1757/1272
2. Sbaffi, L., Walton, J., Blenkinsopp, J., & Walton, G. Information overload in emergency medicine physicians: A multisite case study exploring the causes, impact, and solutions in four North England national health service trusts. JMIR Publications 2020;22(7):1-18.

   https://doi.org/10.2196/19126
3. Lundervoid, A. S., & Lundervoid, A. An overview of deep learning in medical imaging focusing on MRI. ScienceDirect. Special Issue: Deep learning in Medical Physics 2019;29(2):102-127. https://doi.org/10.1016/j.zemedi.2018.11.002
4. Drukker, L., Sharma, H., Droste, R., Alsharid, M., Chatelain, P., Alison Noble, & Papageorghiou, A.T. Transforming obstetric ultrasound into data science using eye tracking, voice recording, transducer motion and ultrasound video. Scientific Reports 2020;11: Article 14109. https://doi.org/10.1038/s41598-021-92829-1
5. Samranvejporn, K. Information system for nurses part 4: Information system in hospital. Rama Nurse Journal 1997;3(1):130-1. https://med.mahidol.ac.th/nursing/jns/DocumentLink/2540/issue_01/11.pdf.
6. Yoheung, D, editors. Practice guide. Storage and delivery of data in accordance with the health information Standards structure version 2.4. 2021. http://spd.moph.go.th/healthdata/wp-content/uploads/2021/03/2.4-43File_Structure-020364.pdf.
7. Lancy, D. Application delivery strategies: Controlling data volume, velocity, and variety. META Group Inc. 2001. https://studylib.net/doc/8647594/3d-data-management--controlling-data-volume--velocity--an
8. Banton, C. Data Science. 2021. https://www.investopedia.com/terms/d/data-science.asp
9. Liao, Q., Zhang, Q., Feng, X., Huang, H., Xu, H., Tian, B. et al. Development of deep learning algorithms for predicting blastocyst formation and quality by time-lapse monitoring. Communications Biology, 2021; Article number 415. https://doi.org/10.1038/s42003-021-01937-1
10. Metkarunchit, T., Charoenpojvajana. K. Detection of covid-19 using deep learning with CT scan images. TNI Journal of Engineering and Technology 2021;8(2):8-17. https://ph01.tci-thaijo.org/index.php/TNIJournal/article/view/243314/165587
11. Fröhlich, H., & Balling. R. From hype to reality: Data science enabling personalized medicine. BMC Medicine 2018; Article number 150;1-15. https://doi.org/10.1186/s12916-018-1122-7
12. Dash, S., Shakyawar, S.K., Sharma, M., Kaushik, S. Big data in healthcare: Management analysis, and future prospects. Journal of Big Data 2019;6(Article number 54):1-25. https://doi.org/10.1186/s40537-019-0217-0
13. Kuan, R. Adopting AI in Health Care Will Be Slow and Difficult. Harvard Business Review. 2019. https://hbr.org/2019/10/adopting-ai-in-health-care-will-be-slow-and-difficult
14. Newman-Token, D. E., Schaffer, A. C., Yu-Moe, C. W., Nassery, N., Tehrani, A. S. S., Clemens, G. D., Wang, Z., Zhu, Y., Fanai, M., & Siegal, D. Serious misdiagnosis-related harms in malpractice claims: The “big three” - vascular events, infections, and cancers. De Gruyter 2019;6(3):227-240. https://doi.org/10.1515/dx-2020-0034
15. Morgan, D. J., Dhruva, S. S., & Coon, E. R. Update on medical overuse: A review. National Library of Medicine

2019;179(11):1568-1574. https://doi.org/10.1001/jamainternmed.2019.3842

16. Mira J J, Carrillo I, Silvestre C, Pérez-Pérez P, Nebot C, Olivera G, et al. Drivers and strategies for avoiding overuse. A cross-sectional study to explore the experience of Spanish primary care providers handling uncertainty and patients' requests. BMJ Open 2017;8(6):1-10. https://doi.org/10.1136/bmjopen-2017-021339
17. Roth A R, Lazris A, Ganatra S Overuse of cardiac testing. American Family Physician 2018;98(10):561-563. https://www.aafp.org/afp/2018/1115/p561.html
18. Burt T, Button K, Noveck R, Munafo M. The burden of the "false-negatives" in clinical development: Analyses of current and alternative scenarios and corrective measures. Clinical and Transitional Science 2017;10(6):470-479. https://doi.org/10.1111/cts.12478
19. Kamal R, Hudman J. editors. Health system tracker. What do we know about spending related to public health in the U.S. and comparable countries? 2020. https://www.healthsystemtracker.org/chart-collection/what-do-we-know-about-spending-related-to-public-health-in-the-u-s-and-comparable-countries/
20. Colclough G, Dorling G, Riahi F, Ghafur S, Sheikh A. editors. Harnessing data science and AI in healthcare: From policy to practice. World Innovation Summit for Health 2018. 2018. https://www.wish.org.qa/wp-content/uploads/2018/11/IMPJ6078-WISH-2018-Data-Science-181015.pdf.
21. Flores M, Glusman G, Brogaard K, Price ND, Hood L. P4 medicine: How systems medicine will transform the healthcare sector society. National Library of Medicine 2013;10(6):565-57. https://doi.org/10.2217/pme.13.57
22. Garner. S. (n.d.). editors. Data science for health and care excellence. National Institute for Health and Care Excellence. https://www.nice.org.uk/Media/Default/About/what-we-do/science-policy-and-research/getreal-uk-data-science-report.pdf
23. Elservier Ltd. 20 years of precision medicine in oncology. The Lancet 2021;397: Article number 10287. https://doi.org/10.1016/S0140-6736(21)01099-0
24. Zachary DS, Skylar YL, Faghi F, Campbell RH, Zhai C, Efron MJ, et al. Big data: Astronomical or genomical?. PLOS Biology 2015. https://doi.org/10.1371/journal.pbio.1002195
25. Bughin J, Hazan E, Ramaswarmy S, Chui M, Allas T, Dahlstrom P, et al. editors. Artificial intelligence: The next digital frontier? McKinsey Global Institution. 2017. https://www.mckinsey.com/~/media/mckinsey/industries/advanced%20electronics/our%20insights/how%20artificial%20intelligence%20can%20deliver%20real%20value%20to%20companies/mgi-artificial-intelligence-discussion-paper.ashx
26. Adler-Milstein J, Pfeifer E. Information blocking: Is it occurring and what policy strategies can address it. Milbank Quarterly 2017;95(1):117-135. https://doi.org/10.1111/1468-0009.12247
27. Panyowat R. editors. Hospital information system (HIS) in Thailand. 2019. https://rath.asia/2019/11/his-vendors-thailand/his-vendor-thai-08/
28. Mehdipour Y. Hospital information system (HIS): At a glance. Asian Journal of Computer Science and Information Technology 2019;1(2). https://www.researchgate.net/publication/329029643_Hospital_Information_System_HISA t_a_Glance
29. Intelligence and Emergency Response Group, Bureau of Occupational and Environmental Diseases, Department of Disease Control Ministry of Public Health. editors. ICD-10 coding for occupational and environmental diseases. 2016.

http://envocc.ddc.moph.go.th/uploads/media/manual/7.ICD10.pdf

30. Thongthai K, Kunawaradisai N, Watcharathanakij S. Adoption of electric health records in medical clinics and dental clinics. Thai Journal of Pharmacy Practice 2017;9(2):490-8. https://he01.tci-thaijo.org/index.php/TJPP/article/view/170920/122833

31. Information and Communication Technology Center, Office of the Permanent Secretary, Ministry of Public Health. (2017). *Health Information Technology Strategy Ministry of Public Health (2017-2026)*. https://ict.moph.go.th/upload_file/files/eHealth_Strategy_THAI_16NOV17.pdf

32. Office for Civil Rights. editors. Hitech Act for Enforcement Interim Final Rule. U.S. Department of Health & Human Service. https://www.hhs.gov/hipaa/for-professionals/special-topics/hitech-act-enforcement-interim-final-rule/index.html

33. Strategic Management services. (n.d.). editors. Hitech Act Update: Medicare and Medicaid EHR Incentive Programs Regulations. https://www.compliance.com/resources/hitech-act-update-an-overview-of-the-medicare-and-medicaid-ehr-incentive-programs-regulations/

34. Theera-Ampornpunt N. Electronic health records: "America is strong" What did it teach Thailand? 2010. https://www.academia.edu/745199/Electronic_Health_Records_อเมริกาเข_มแข_ง_สอนอะไรไทย

35. Wang Sam Mo Hospital. Summary of problems from recording 43 files and solutions. 2020. https://www.wangsammohospital.go.th/article_detail.php?id=12

36. Rojanasaksothorn. S. Request for review and correction of information on M&E issues. 3rd committee, Round 1/2020. 2020. https://www.healthregion10.moph.go.th/wp-content/uploads/2020/04/สธ-0235_503-วันที่-21-เมษายน-2563-เรื่องขอให้ตรวจสอบและแก้ไขข้อมูลตามประเด็น-ME-คณะที่-3-รอบที่-1_2563.pdf

37. Yuenyongsuwan M. Analyzing the quality of disease coding (ICD-10-TM) in health data centers. Journal of Health Research and Development Nakhon Ratchasima Public Health Provincial Office 2017;3(2): 63-72. https://thaidj.org/index.php/JHRDNR/article/view/6004

38. Habusaya S,Ditcharoen N. Analysis of ICD-10 coding errors in 43 files database systems for medical record department using data mining techniques. KKU Science Journal, 2020;8(1):141-155. http://203.157.196.7/web_ssj/webmanager/uploads/2018-03-2614320043_Data_Analytic.pdf

39. Wipak R, Turnbull N, Siwina S. Factors related to data quality management for 43 public health data. The Southern College Network Journal of Nursing and Public Health 2017;4[Special Issue]:162-179. https://he01.tci-thaijo.org/index.php/scnet/article/view/84900/67644

40. Rommaneeyapech S, Srilachai S. Program ICD NAVIGATOR VERSION 6.1.1. Medical Journal of Srisaket Surin Buriram Hospitals 2020;35(2):281-289. https://he02.tci-thaijo.org/index.php/MJSSBH/article/view/241310/166208

Volume 4, Issue 5; September-October 2021; Page No 645-652