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Optimizing the Electronic Health Records Through Big Data Analytics: A Knowledge-Based View

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ABSTRACT Many hospitals are suffering from ineffective use of big data analytics with electronic health records (EHRs) to generate high quality insights for their clinical practices. Organizational learning has been a key role in improving the use of big data analytics with EHRs. Drawing on the knowledge-based view and big data lifecycle, we investigate how the three modes of knowledge can achieve meaningful use of big data analytics with EHRs. To test the associations in the proposed research model, we surveyed 580 nurses of a large hospital in China in 2019. Structural equation modelling was used to examine relationships between knowledge mode of EHRs and meaningful use of EHRs. The results reveal that know-what about EHRs utilization, know-how EHRs storage and utilization, and know-why storage and utilization can improve nurses' meaningful use of big data analytics with EHRs. This study contributes to the existing digital health and big data literature by exploring the proper adaptation of analytical tools to EHRs from the different knowledge mode in order to shape meaningful use of big data analytics with EHRs.

INDEX TERMS Big data analytics, electronic health records and impacts, knowledge-based view.

I. INTRODUCTION

With the aim of improving quality of care through the meaningful use of electronic health records (EHRs), the China government has promulgated the Electronic Health Record Architecture and Data Standard in 2009 as a guide for the hospitals. In this guide, EHRs are defined as "a complete collection of digital clinical information documenting the clinical care rendered to an individual in the Chinese EHR Standard" [1]. Over two decades, EHRs has been suggested to enhance the healthcare service efficiency and effectiveness, but it does not mean that simply adopting the EHRs system could lead to those benefits. Healthcare providers need to make the EHR a routine in the daily work system in order to realize the payback. Thus, Health Information Technology for Economic and Clinical Health (HITECH) Act introduces the "meaningful use" of EHR as the goal of adoption. The main objective of Act is to create meaningful and useful digital medical records, including the entry and storage of EHRs, and optimize the utilization of EHRs.

As of 2011, clinical data had reached 150 exabytes (1 EB = 1018 bytes) worldwide, mainly in the form of EHRs [2]. Yet, considerable uncertainty still remains about the use of big data analytics within EHRs and its impact on clinical performance [3]. Such struggles are due to not only insufficient fund and biased resource allocation at the national level but also lack of planning and governance for the use of big data analytics within EHRs at the hospital level [3], [4].

To address this challenge, although many hospitals in China have invested a great deal of cost, time and resources in learning the implementation and utilization of EHRs, they are still suffering from ineffective use of big data analytics within EHRs to generate high quality information for decision making and reduce health disparities [3], [9]. One of the key reasons for this difficulty is the lack of full consideration of EHRs fitness to the specific situations of the particular organization [9]. It is important for healthcare practitioners to pay greater attention to understand how to absorb the diverse

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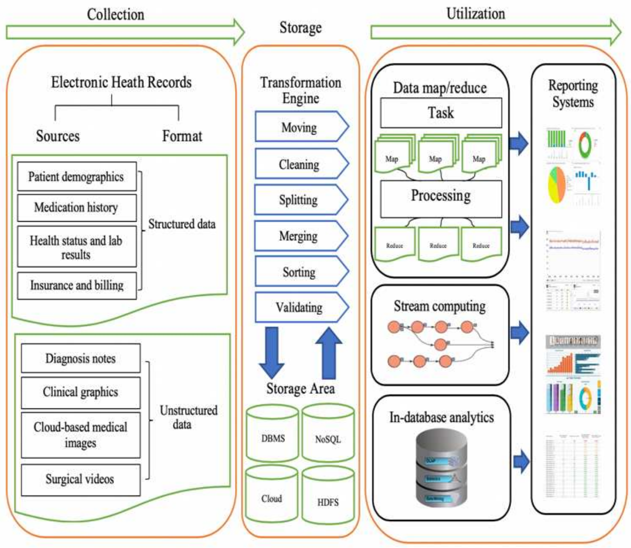

FIGURE 1. Optimizing the electronic health records through big data analytics.

knowledge of EHRs. As such, little attention has been paid to understanding the role of knowledge mode in improving the use of big data analytics within EHRs. In this study, thus, we examine the relationship between the knowledge about big data analytics within EHRs and the outcome of EHRs adoption (i.e., meaningful use of EHRs).

The remainder of this paper is structured as follows: the next section serves as our theoretical background, which leads to the development of the research model and associated hypothesis; followed by our research method, findings and discussions, contributions to research, implications for practice and recommendations, then limitations and future research directions are discussed as our conclusion.

II. OPTIMIZING THE ELECTRONIC HEALTH RECORDS THROUGH BIG DATA ANALYTICS

The meaningful use of EHRs is crucial for improving clinical operations and healthcare service [5]. Big data analytics is a tool that enables healthcare organizations to reach this goal by optimizing EHRs through analytical algorithms. For example, Texas Health Harris Methodist Hospital Alliance utilizes medical sensor data to analyze patients' movements and monitor their actions throughout their hospital stay. In this way they can provide healthcare services more efficiently and accurately, optimize existing operations, and prevent some medical risks [6]. Indeed, the use of big data analtyics within EHRs is rooted in the concept of data life cycle framework that consists of three components: data collection, data storage, and data utilization, as shown in Figure 1. These logical components that perform specific functions enable healthcare practitioner to understand how to transform the EHRs into meaningful clinical insights through big data analtyics.

Data collection. This component contains all the data sources and content type of EHRs. In general, The EHRs are divided into structured data (e.g., patient demographics, medication history, health status and lab results) and unstructured data (e.g., diagnosis notes, clinical graphics, and medical images). These data are collected from various clinical units inside the hospital or from external units.

Data storage. The EHRs are stored into appropriate databases depending on the source of data and content format. This component aims to handle data from the various data sources by two steps: transformation and storage. The transformation engine is capable of moving, cleaning, splitting, translating, merging, sorting, and validating EHRs. For instance, structured EHRs data will be extracted from healthcare information systems and converted into a specific standard data format, sorted by the criterion (e.g., patient identity, health status medication history), and then the record in the right place. In the next step, the EHRs are loaded into the target databases (e.g., Database Management System; DBMS, Hadoop distributed file systems; HDFS, or in a cloud) for further analysis.

Data Utilization. This component is used to process all kinds of EHRs and report the summarized results for clinical decision making. The analysis of EHRs includes Map/Reduce, stream computing, and in-database analytics, depending on the type of data and the purpose of the analysis. Map/Reduce can provide the ability to process massive unstructured and structured EHRs in batch form in a massively parallel processing environment. Stream computing can support near real time or real time analysis for EHRs. Though stream computing, medical staffs can track EHRs in motion in order to respond to unexpected events and determine next-best actions. In-database analytics is commonly used data mining approach that allows EHRs to be analyzed within database. It can provide high-speed parallel processing and offer a safe environment to process confidential patient information. This component also generates various visualization reporting and real-time and meaningful business insights derived from the analysis. The reporting system is a critical big data analtyics feature that allows EHRs to be visualized in a meaningful way to support medical staff day-to-day operations and clinical decisions.

III. RESEARCH MODEL AND HYPOTHESIS DEVELOPMENT

Prior research has acknowledged that organizational learning has been an important enabler for improving the use of big data analytics within EHRs [7]–[9]. From the aspect of information technology (IT) adoption, learning process plays a key role in the outcomes of the IT adoption. When the new IT is introduced to the organization, it implies that a large amount of knowledge is brought in [10], [11]. Organizations need to adopt a series of learning processes to merge the gap between what needs to be known and what is already known in order to understand how to use this knowledge effectively and efficiently [10]. From the knowledge-based view (KBV), knowledge plays a pivotal role in increasing the organizations' competitive advantage and financial performance [12], [13]. Effective knowledge activities in healthcare

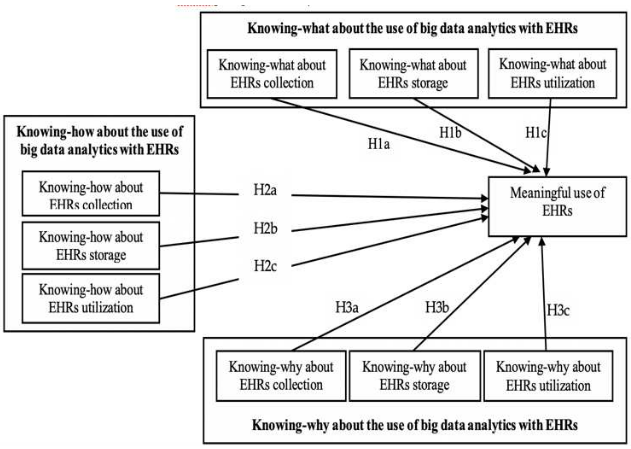

FIGURE 2. Proposed model of how three mode of knowledge about the use of big data analytics within EHRs for achieving meaningful use of EHRs.

not only improve the existing operational capabilities of healthcare service but also reduce the care delivery costs and prevent potential medical errors [14], [15].

Drawing on the knowledge-based view (KBV), we develop our research model and associated hypotheses, as shown in Figure 2. KBV posits that organizational knowledge is viewed as a strategic resource of an organization. It also emphasizes that creating knowledge for the production of goods and services can acquire competitive advantage and organizational performance [12], [15]. In the context of EHRs implementation, an effective knowledge creation from EHRs is likely to be achieved by all medical staffs knowing how, why, what EHRs can be used properly.

To understand the creation of knowledge, it is essential to explore the mode of knowledge. In general, the mode of knowledge activities can be classified into three categories according to the level of material involvement with the knowledge: knowing-what, knowing-how, and knowing-why [18]. Knowing-what refers to a declarative knowledge that contains information about activities and relationships [18]. This knowledge allows organizations to understand the digital health technologies in certain detail, such as the principle and characteristics of the technology, and to generate to a certain tangible products or outcomes. In the context of EHRs, hospitals need to understand what EHRs are, its features, and problems when it applies in practice. When they learn about EHRs, hospitals would perceive an attitude towards it and form the basic idea of how to adopt it effectively. Thus, we propose the following hypotheses.

Hypothesis 1a (H1a): Knowing-what about the data collection of EHRs will facilitate meaningful use of EHRs.

Hypothesis 1b (H1b): Knowing-what about the data storage of EHRs will facilitate meaningful use of EHRs.

Hypothesis 1c (H1c): Knowing-what about the data utilization of EHRs will facilitate meaningful use of EHRs.

Knowing-how is a procedural knowledge that includes the step-by-step procedures executable in a specific system [16]. Data analysts within healthcare organizations need to gain this type of knowledge in order to process EHRs effectively and meaningfully. For example, Tracking EHRs can generate real-time monitoring patient information such as alerts and proactive notifications. Data analysts need to know what the most important outputs are and how to display them and send to interested users or made available in the form of dashboards in real time. Knowing-how about processing EHRs can explore patterns of care and provide exceptional support for evidence based medical practices. Using knowing-how, healthcare organizations can also address data quality issue through knowing well-defined procedures and rules in an EHRs system. Thus, we propose the following hypotheses.

Hypothesis 2a (H2a): Knowing-how about the data collection of EHRs will facilitate meaningful use of EHRs.

Hypothesis 2b (H2b): Knowing-how about the data storage of EHRs will facilitate meaningful use of EHRs.

Hypothesis 2c (H2c): Knowing-how about the data utilization of EHRs will facilitate meaningful use of EHRs.

Knowing-why is a contextual knowledge that enables users to solve the problems based on understanding contextual reasons and axiomatic principles [16], [17]. This knowledge provides explanations for rationalization about technology. In the context of EHRs, hospitals realize why EHRs should be used to generate better clinical performance. This includes the examination of the specific situation of their organizations and comparison of other alternative solutions. Also, organizations should be aware of the impacts and consequences of utilizing EHRs. Besides the financial and organizational impact of EHRs, hospitals also have to harness the possible challenges when they use the EHRs system. In hospitals, a high level of knowing-why about EHRs can be accumulated by understanding of knowing-what and knowing-how involved in data collection, storage, and utilization of EHRs in the clinical system. Thus, we propose the following hypotheses.

Hypothesis 3a (H3a): Knowing-why about the data collection of EHRs will facilitate meaningful use of EHRs.

Hypothesis 3b (H3b): Knowing-why about the data storage of EHRs will facilitate meaningful use of EHRs.

Hypothesis 3c (H3c): Knowing-why about the data utilization of EHRs will facilitate meaningful use of EHRs.

IV. METHODS

A. SAMPLE AND DATA COLLECTION

We investigate the relationship between knowledge mode of EHRs and meaningful use of EHRs among healthcare workers in China, primarily surveyed nurses after receiving ethics approval. An initial population set of 1,000 nurses was obtained from a large hospital in Henan province, China. The first round of 1,000 questionnaires resulted in 351 invitations being rejected due to the availability. Of the 649 invitations that were seen by potential respondents, 580 responses were returned, completed and usable for the data analysis, showing a response rate of 89.37%.

TABLE 1. Demographic characteristics of the final sample with information of the participants (*n* = 580).

Demographic characteristics		Frequency	Percentage (%)
Gender	Male	80	13.80%
	Female	500	86.20%
Age	<25	135	23.30%
	25~30	234	40.30%
	31~35	126	21.70%
	36~40	40	6.90%
	41~45	13	2.20%
	46~50	17	2.90%
	>50	15	2.60%
Education	Below College	46	7.90%
	Bachelor Degree	164	28.30%
	Master Degree	355	61.20%
	Doctor Degree	11	1.90%
	Missing	4	0.70%
Working Age (Year)	<3	152	26.20%
	3~5	147	25.30%
	6~10	183	31.60%
	11~20	59	10.20%
	>20	39	6.70%
Department	Internal Medicine	193	33.28%
	Surgical	104	17.93%
	Maternity	44	7.59%
	Pediatric	28	4.83%
	Chinese Medicine/Rehabilitation	28	4.83%
	Infection/Oncology	45	7.76%
	Other Clinical Department	49	8.45%
	Medical Technician	22	3.79%
	Administration and Logistics	59	10.17%
	Other	8	1.38%

Non-response bias was assessed by comparing the first 25 percent with the last 25 percent of the responses for each variable using paired sample t-tests [18]. The results showed no statistically significant difference ($p > 0.05$) between these two groups, indicating that non-response bias did not present a problem for this study.

The demographic characteristics of the respondents are shown in Table 1. Among the 580 respondents, 86.20% were female. Most nurses (92.20%) were younger than 40 years: 23.30% were younger than 25 years, 40.30%were 25–30 years of age, 21.70% were 31–35 years of age, and 6.90% were 36–40 years of age. Most respondents had a bachelor's degree (91.40%). The respondent seniority (years of employment) was evenly distributed, and the largest group had a seniority of 6–10 years (31.60%). A plurality of respondents (33.28%) worked in the internal medicine department.

B. VARIABLES AND INSTRUMENTS

The instrument used in this study was adapted from previously validated instruments (presented in Appendix 5). All independent and dependent variables were collected using an online survey completed by each participant. The scale of knowing-what, knowing-how, and knowing-why about EHRs was adapted from Lee and Strong's study [16] who proposed the three mode of knowledge underlying data collection, storage, and utilization and examined how knowledge held by different work roles affects data quality. This scale was used to rate the knowledge level of EHRs by which each participant acquires. A seven-point Likert-type scale was used to capture the responses, ranging from 1 = very small extent, through 4 = average, to 7 = very large extent.

The measurement of meaningful use of the EHR was developed from the regulation published by Department of Health and Human Services (DHHS) for the year 2011-2012 [19]. Leading by Centers for Medicare and Medicaid Services, DHHS developed a list of criteria for meaningful use requirements on January 16, 2010 based on the call from Health Information Technology for Economic and Clinical Health (HITECH). Five items were developed according to those regulations to measure the performance of the adopted EHRs in hospital. A seven-point Likert-type scale was used to capture the responses, ranging from 1 = strongly disagree to 7 = strongly agree.

C. MEASUREMENT VALIDITY AND RELIABILITY

The validity and reliability of measurements were assessed from the sample data set ($n = 580$) collected for this study. As shown in Table 2, the loadings are all within acceptable ranges, and all but three items for knowing-what about EHRs storage, knowing-what about EHRs utilization, and knowing-how about EHRs utilization have loadings above the threshold of 0.5. All of the reliability coefficients (Cronbach's alphas) are above 0.80 (Table 2), confirming that the measurements are reliable. The correlations for each construct are presented in Table 3.

Convergent validity was assessed by three criteria: (1) item loading; (2) composite reliability; and (3) average variance extracted (AVE) [20]. The composite reliability scores range from 0.579 to 0.881. Each AVE is above 0.4, but KHEU (Table 2), which is acceptable. We assessed discriminant validity by checking whether each item loads more highly on its assigned construct than on other constructs, as suggested by Gefen, Straub and Boudreau [21]. Each item loading in the cross-loading table is markedly higher on its assigned construct than on the other variables. Thus,

TABLE 2. Reliability and validity measures of the research model.

Variable	Mean	S.D.	Alpha	CR	AVE
KWEC	4.498	1.387	0.891	0.811	0.466
KWES	4.210	1.517	0.915	0.795	0.440
KWEU	4.744	1.421	0.885	0.755	0.440
KHEC	3.971	1.416	0.891	0.748	0.417
KHES	4.060	1.575	0.955	0.880	0.596
KHEU	4.080	1.570	0.925	0.579	0.314
KWhyEC	4.185	1.511	0.941	0.791	0.487
KWhyES	4.083	1.506	0.962	0.857	0.462
KWhyEU	4.161	1.538	0.962	0.881	0.553
MUE	4.189	1.470	0.889	0.807	0.457

Note: N=580; CR: Composite reliability; Alpha: Cronbach's alpha; S.D.: Standard deviation; AVE: Average variance extracted

TABLE 3. Inter-construct correlations.

Variable	1	2	3	4	5	6	7	8	9	10
KWEC	1									
KWES	0.70	1								
KWEU	0.72	0.71	1							
KHEC	0.61	0.72	0.65	1						
KHES	0.48	0.61	0.50	0.75	1					
KHEU	0.55	0.68	0.59	0.76	0.75	1				
KWhyEC	0.50	0.58	0.47	0.63	0.59	0.65	1			
KWhyES	0.52	0.65	0.49	0.71	0.67	0.71	0.81	1		
KWhyEU	0.52	0.61	0.50	0.68	0.64	0.66	0.67	0.77	1	
MUE	0.47	0.61	0.55	0.65	0.65	0.68	0.59	0.68	0.69	1

Note: All inter-construct correlations are significant at the 0.01 level (2-tailed)

our measurements demonstrate acceptable discriminant and convergent validities.

In addition, we assessed the potential effect of common method bias statistically by conducting Harman's one-factor test [22] generated ten principal constructs; the unrotated factor solution shows that the first construct explains only 11.11% of the variance, indicating that our data do not suffer from high common method bias. Consequently, this test suggest that common method bias is not a major concern for this study.

V. RESULTS

The results from the regression analysis are shown in Table 4. The hypotheses were assessed by checking the direction and significance of path coefficients (β) between dependent and independent variables. Our proposed research model is a good predictor of meaningful use of EHRs in the context of nursing department as the R2 accounts for 60.70% of the variance. According to the results, we found that different modes of knowledge can be used to improve nurses' effective use of EHRs. For example, our finding reveals that know-what, know-how and know-why about EHRs utilization can lead improved meaningful use of EHRs, thus H1c, H2c, and H3c are supported. This implies that EHRs utilization plays an important role in developing meaningful use of EHRs practice. In addition to the EHRs utilization, we also found that if nurses know how and why EHRs are stored, they are most likely to use EHRs effectively. Thus, H2b and H3b are supported. Surprisingly, knowing what, how, and why about how EHRs are collected does not improve meaningful use of EHRs, which H1a, H2a, and H3a are not supported.

TABLE 4. Standardized regression coefficients β) with p value (α0.05).

Paths	Standardized β	t value	p value	Results
H1a: KWEC→MUE	-0.105	-2.508	0.012*	Not supported
H1b: KWES→MUE	0.077	1.637	0.102	Not supported
H1c: KWEU→MUE	0.167	3.834	0.000***	Supported
H2a: KHEC→MUE	0.006	0.115	0.909	Not supported
H2b: KHES→MUE	0.158	3.570	0.000***	Supported
H2c: KHEU→MUE	0.173	3.623	0.000***	Supported
H3a: KWhyEC→MUE	0.000	-0.004	0.997	Not supported
H3b: KWhyES→MUE	0.164	2.907	0.004**	Supported
H3c: KWhyEU→MUE	0.266	6.052	0.000***	Supported

Notes: * p<.05; ** p<.01; ***p<.001

VI. THEORETICAL AND PRACTICAL CONTRIBUTIONS

To strategically meaningful use of EHRs, prior work has developed many analytical approaches to effectively process EHRs. However, what kind of knowledge about the use of big data analtyics within EHRs should be created remains unknown. By addressing this research gap, the theoretical and practical contributions of this study are three-fold. Firstly, our findings have partially confirmed knowledge about the use of big data analytics within EHRs matters for meaningful use of EHRs. This is among the first study to investigate the use of big data analytics within EHRs from a knowledge-based view. Three mode of knowledge about the use of big data analytics for EHRs are identified and tested their impact on improving meaningful use of EHRs practices. Based on our findings, healthcare organizations can make a strategic decision as to which type of knowledge and big data analytics components need to be enhanced to improve meaningful use of EHRs. For example, improving meaningful use of EHRs does not require nurses to understand how, why, and what EHRs are collected within a hospital.

Secondly, we found meaningful use of EHRs is highly influenced by knowing-what, knowing-how and knowing-why about data utilization of EHRs as generally reflected in common sense. It is particularly important to gain knowledge regarding why various analtyics such as descriptive analtyics and predictive analtyics can be used for EHRs. This result is consistent with Lee and Strong's [16] finding who recognizes the critical role that knowing-why plays in producing high data quality. Indeed, constant increasing large volume of EHRs is challenging healthcare organization's data management capabilities [23]–[26]. Needs for knowing-why about data utilization of EHRs is not unique for healthcare

TABLE 5. The items in the questionnaire and the results of EFA.

	Items	Factor loadings
Knowing-what about EHRs collection (KWEC) [9]	KWEC01: I know who creates EHRs.	0.772
	KWEC02: I know which group collects EHRs.	0.747
	KWEC03: I know the procedures by which EHRs are collected.	0.694
	KWEC04: I know the steps taken to gather EHRs.	0.569
	KWEC05: know the sources of EHRs.	0.610
Knowing-what about EHRs storage (KWES) [9]	KWES01: I know who maintains EHRs in our systems.	0.625
	KWES02: I know which group maintains EHRs in our systems.	Deleted
	KWES03: I know the procedures used to store EHRs in our systems.	0.751
	KWES04: I know the steps taken to store EHRs in our systems.	0.730
	KWES05: I know which of our computers stores EHRs	0.630
	KWES06: I know which software is used for storing EHRs in our systems.	0.563
Knowing-what about EHRs utilization (KWEU) [9]	KWEU01: I know who (individual or group) uses EHRs.	0.761
	KWEU02: I know which group uses EHRs.	0.717
	KWEU03: I know the procedures in which EHRs are used.	0.528
	KWEU04: I know the steps taken when using EHRs.	Deleted
	KWEU05: I know the tasks which require the use of EHRs.	0.620
Knowing-how about EHRs collection (KHEC) [9]	KHEC01: When typical problems arise with collecting EHRs, I know how we handle them.	0.555
	KHEC02: I know the usual solutions for problems with collecting EHRs.	0.697
	KHEC03: I know how to fix routine problems with collecting EHRs.	0.573
	KHEC04: I know how to fix recurring problems with collecting EHRs.	0.621
	KHEC05: I know the standard procedures for correcting deficiencies in EHRs when collecting them.	0.575
Knowing-how about EHRs storage (KHES) [9]	KHES01: When typical problems arise with storing EHRs in our systems, I know how we handle them.	0.769
	KHES02: I know the usual solutions for problems with storing EHRs in our systems.	0.752
	KHES03: I know how to fix routine problems with storing EHRs in our systems.	0.766
	KHES04: I know how to fix recurring problems with storing EHRs in our systems.	0.784
	KHES05: I know our standard procedures for correcting deficiencies in EHRs when storing them in our systems.	0.788
Knowing-how about EHRs utilization (KHEU) [9]	KHEU01: When typical problems, such as interpretation or access, arise with using EHRs, I know how we handle them.	0.573
	KHEU02: I know the usual solutions for problems with using EHRs.	0.568
	KHEU03: I know how to fix routine problems with using EHRs.	0.540
	KHEU04: I know our standard procedures for correcting deficiencies in EHRs when using them.	Deleted
Knowing-why about EHRs collection (KWhyEC) [9]	KWhyEC01: I know the problems encountered in collecting EHRs.	0.699
	KWhyEC02: I understand EHRs collection procedures well enough to recognize why EHRs are collected incorrectly.	0.701
	KWhyEC03: I can detect sources of new problems in collecting EHRs.	0.706
	KWhyEC04: I can recognize new problems as they arise in collecting EHRs.	0.685
Knowing-why about EHRs storage (KWhyES) [9]	KWhyES01: I know why EHRs are displayed in this form in our systems.	0.649
	KWhyES02: I know some of the problems in storing EHRs appropriately in our systems.	0.655
	KWhyES03: I know why it is difficult to store EHRs in our systems in an easy-to-interpret manner.	0.688
	KWhyES04: I understand our computing environment well enough to analyze why EHRs are stored inadequately.	0.691
	KWhyES05: I can recognize new problems as they arise in storing and maintaining EHRs in our systems.	0.715
	KWhyES06: I know why people have difficulty with system access procedures for EHRs.	0.711
	KWhyES07: I know why it is difficult to store all EHRs in our systems.	0.647

TABLE 5. ***(Continued.)*** **The items in the questionnaire and the results of EFA.**

Knowing-why about EHRs utilization (KWhyEU) [9]	KWhyEU01: I know some of the problems in ensuring that EHRs are used appropriately.	0.685
	KWhyEU02: I can detect sources of new problems in using EHRs.	0.710
	KWhyEU03: I can recognize new problems as they arise in using EHRs in a new task.	0.769
	KWhyEU04: I can diagnose problems in using EHRs.	0.763
	KWhyEU05: I can find the causes of new problems in the use of EHRs.	0.765
	KWhyEU06: I can recognize when new problems arise in using EHRs in a new task.	0.767
Meaningful use of EHRs (MUE) [17]	MUE01: Majority of patients' data, including the demographic, vital signs, up-to-date problem and diagnoses, medication, allergy list, and smoking status, is recorded as computerized data.	0.592
	MUE02: Our patients typically have their clinical procedures and medications ordered through computerized provider order entry systems.	0.724
	MUE03: Our clinical information such as diagnoses, lab and test results, and images can be electronically exchanged with external clinical providers and patient-authorized entities.	0.717
	MUE04: The computerized EHRs used by us can help with clinical decision support, for example, allergy alert, drug interaction.	0.694
	MUE05: EHRs can be exchanged with different public health entities, for example, reportable lab, immunizations.	0.645

but more important because the results extracted from the analysis of EHRs concerns patients' quality of care and well-being. A poor data utilization of EHRs may lead to issues such as billing errors, intentional frauds, or medical mistakes.

Thirdly, our findings show that knowledge about data collection of EHRs does not matter for improving meaningful use of EHRs. A potential explanation is that in practice nurses are data collectors that know more about collecting accurate and complete healthcare records. Thus, knowledge about how to collect EHRs would not play an important role in improving meaningful use of EHRs. Instead, they are interested in knowing more about making data relevant to their daily clinical tasks.

VII. CONCLUSION

This study has some limitations that may create interesting opportunities for future research. First, this study only collects data from a large hospital as the research sample. Although sufficient number of data points and high response rate may represent a large portion of population in a region of China, there is still a need to collect the data from the different hospitals to better generalize our research findings. Future research may assess potential difference among age groups, among working experience groups, and among different clinical department groups, with a more representative sample. Second, future research could consider applying qualitative methods to complement the general lack of adequate survey methods. Third, examining the knowledge mode of EHRs with linear methods does not support the comprehensive view required to capture the non-linear interaction among these knowledge modes [6]. Future research could consider using fuzzy-set Qualitative Comparative Analysis as a data analysis approach to better explain how different knowledge mode of EHRs simultaneously combine to achieve meaningful use of EHRs.

Our study contributes to the existing digital health, big date literature and nursing literature in three ways. First, this research explores the proper adaptation of analytical tools to EHRs from the different knowledge mode in order to improve meaningful use of big data analytics within EHRs [29], [30]. Second, we identified the important the knowledge modes of EHRs (e.g., know-how, know-what, and know-why about EHRs utilization) that provides evidence regarding the ways in which how training programs/course of EHRs can be designed [29]. This also extends and deepens understanding of how meaningful use of EHRs practices can be improved [30]. It could be a useful guidance for hospital practitioners, outlining a variety of knowledge mode of EHRs that they can focus [23], [31], [32]. Third, this research proposes a conceptual model with a knowledge-based view to explicate the different knowledge mode of EHRs in the meaningful use of EHRs practice for nursing professionals. To the best of our knowledge, as yet, no previous studies have considered the knowledge mode of EHRs driving meaning use of EHRs in the nursing context.

APPENDIX

See Table 5.

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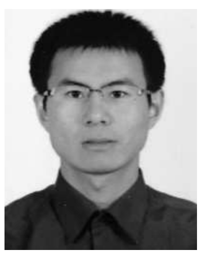

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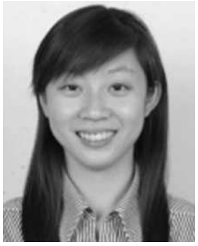

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